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ORIGINAL ARTICLE

Mobile Location-Based Services' Value-in-Use in Inner Cities: Do a Customer's Shopping Patterns, Prior User Experience, and Sales Promotions Matter?

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Abstract Mobile location-based services (LBS) represent a promising opportunity for inner-city retailers and service providers to react to changes in customer behavior due to digitalization. To gain competitive advantages, mobile LBS must offer customers high value-in-use and help them reach their shopping goals during their inner-city visits. Shopping goals differ depending on shopping patterns; thus, these patterns may influence customers' evaluation of mobile LBS during inner-city visits. Since value-in-use is not only a context-specific but also a temporally dynamic construct, customers' user experience must also be considered. Therefore, this study investigates the influence of customers' shopping patterns and current user experience on their evaluation of mobile LBS' value-in-use during inner-city visits. Moreover, the impacts of the offers transmitted through mobile LBS on the value-in-use are examined.

Using field test data, we empirically verify a conceptualization of mobile LBS and determine a comprehensive view of mobile LBS' value-in-use during shopping trips with different shopping patterns and user experience within a mixed-method analysis. Our results identify both utilitarian and hedonic value-in-use components as being empirically relevant for high value-in-use evaluations regarding mobile LBS

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in inner cities. Furthermore, the relevance of monetary benefits, fun benefits, and irritation on value-in-use vary according to customers' user experience. A customer's shopping pattern affects the value-in-use of mobile LBS; however, this effect is not as differentiated as expected. Moreover, the number of relevant monetary and non-monetary offers transmitted during an inner-city visit are shown to represent a potential, albeit limited, management instrument for affecting mobile LBS' value-in-use.

Keywords Value-in-Use · Mobile Location-Based Services · Shopping Patterns in Inner Cities · Sales Promotions · Fuzzy-Set Qualitative Comparative Analysis

JEL M31 · M37 · L81

1 Introduction

Inner cities are one of the most crucial shopping channels for consumers. For this reason, inner-city retail contributes significantly to a city's economic efficiency by creating jobs and generating corporate and income taxes (Porter 1995), leading to interdependences between inner-city prosperity and retail as well as shaping the relevance of retail. Inner-city retailing acts as a catalyst that determines an inner city's attractiveness (Warnaby et al. 2005) and positively affects visit frequency (Teller and Elms 2010; Teller and Reutterer 2008). Additionally, the inner city's multifunctionality as a place in which to live, work, and spend leisure time strengthens the quality of the time a consumer spends there (Betzing et al. 2018), contributing to increased attractiveness (De Nisco and Warnaby 2013; Teller and Elms 2010; Teller and Reutterer 2008; Warnaby et al. 2005) and securing the business base in the retail sector. The combination of shopping and other activities and social interactions make the inner city an attractive shopping destination (Hart et al. 2013). Due to inner cities' social relevance, it is important to maintain them as shopping hubs and ensure that they remain attractive. This paper investigates a potential way to preserve the inner city by applying location-based services (LBS) as a new digital technology.

Notably, shopping behaviors have changed, especially with the advent of digital technologies and the increased use of mobile devices by consumers (Faulds et al. 2018; Hagberg et al. 2016). Particularly, the rise of mobile devices has altered the retail landscape by changing business opportunities and models, commerce forms, and purchasing processes (Hagberg et al. 2016). Today, customers are more informed, independent, and demanding, which has led to higher expectations being placed on retailers (Faulds et al. 2018). The ease of access to the Internet via smartphones has also changed customers' behaviors at physical stores (Hagberg et al. 2016). For example, customers now use their smartphones to search for product information and prices, check product ratings, compare products, and consult family and friends for advice directly in-store (Mosquera et al. 2018). Furthermore, consumers use multiple channels to interact with retailers and are "willing to move seamlessly between channels—traditional store, online, and mobile—depending on their preferences, their current situation, the time of day, and the product category" (Silva et al. 2019, p. 1).

To counter these trends and offset some of online retailing's advantages, inner-city retailers need to better meet their customers' expectations by enabling new forms of digital customer interaction (Betzing et al. 2018; Pura 2005). One promising opportunity to do this is to provide mobile LBS through a local multi-sided digital community platform that connects local customers, inner-city retailers, and other inner-city stakeholders (Bartelheimer et al. 2018). *Mobile LBS* are "any kind of network-based, mobile information services that account for and result from the positional information taken from a mobile device to provide value-added services to users, depending on their geographic context and individual preferences" (Ryschka et al. 2016, p. 233). The use of mobile LBS may create new, digital customer touchpoints, enabling more active design and support of the entire customer journey through inner-city retailing (Faulds et al. 2018; Kang et al. 2015). However, to achieve these competitive advantages, customers need to actually use mobile LBS; in other words, mobile LBS must offer customers high value-in-use (e.g., Kleinaltenkamp et al. 2018; Macdonald et al. 2011, 2016; Bruns and Jacob 2014). In line with current research, we assume that value-in-use is a trade-off between benefits and sacrifices, which a customer perceives within the scope of achieving context-specific goals in the usage process (Sweeney et al. 2018; Macdonald et al. 2016). Here, both utilitarian (avoiding negative consequences and increasing efficiency) and hedonic (seeking pleasure) aspects related to the achievement of the goals of this usage are relevant (Macdonald et al. 2016; Chitturi et al. 2008). Against the backdrop of value-in-use as a context-specific and temporally dynamic construct, the specific usage situation and its underlying goals, as well as prior service experiences, are accorded high priority (Macdonald et al. 2016; Grönroos and Voima 2013; Helkkula et al. 2012a, b). To address this, inner-city visitors' shopping patterns during specific visits in which mobile LBS are used should be examined as a possible context factor. Additionally, the customer's evaluation of value-in-use over the entire usage history—and thus at the various service events—should be considered in order to gain a comprehensive understanding of value-in-use and its evolution. In addition to knowledge of the composition of value-in-use, the possibility of influencing it is relevant from the perspective of inner-city retail. Offers transmitted through mobile LBS represent a possible management instrument, as this is a central mobile LBS function and thus may be a possible value driver.

While many extant studies have focused on the conceptualization and operationalization of perceived value, few have examined value-in-use in the business-to-consumer realm (e.g., Sweeney et al. 2018; Bruns and Jacob 2016). Most of the extant literature on value-in-use is either conceptual or exploratory (Hartwig and Jacob 2018; Kleinaltenkamp et al. 2018; Bruns and Jacob 2016; Gummerus and Pihlström 2011; Macdonald et al. 2011). Moreover, while innovation adoption research has examined customers' acceptance and use of LBS, it has only looked into customers' intention to use this technology, not value-in-use. Nevertheless, some studies have focused on mobile apps' value-in-use in various usage contexts (e.g., Fang 2019; Bruns and Jacob 2014). Additionally, evidence has been found that previous user experiences have a moderating effect on the evaluation and use of mobile apps (e.g., Hart and Sutcliffe 2019; Newman et al. 2018; Workman 2014). To our knowledge, studies concerning the effects of user experience on value-in-use and their temporally dynamic nature in the context of LBS have not been conducted, and no studies have examined the impact of shopping patterns on value-in-use in this context. Furthermore, a full body of research already exists on sales promotions, dealing with customer perceptions, and thereby examining the value-adding properties of sales promotions (e.g., Sinha and Verma 2020; Reid et al. 2015; Chandon et al. 2000). A clear link between the type and number of mobile LBS-provided sales promotions and value-in-use has, to our knowledge, not yet been established or empirically investigated. In summary, there is an ongoing research gap regarding mobile LBS' value-in-use and the role of goal-oriented shopping patterns and customers' current user experience during inner-city visits. Further, there is a lack of specific knowledge regarding the usefulness of relevant offers transmitted through the mobile LBS that positively influence value assessment.

To address this gap, the current study explores whether mobile LBS' value-in-use in an inner city depends on customers' shopping patterns during inner-city shopping trips as well as their user experience. Furthermore, this study examines the potential of the transmission of relevant information and offers to manage mobile LBS' value-in-use in inner cities. Therefore, this study has five main objectives: The first objective is the identification of relevant value-in-use components of mobile LBS in inner cities and inner-city shopping patterns. The second objective is to validate the conceptualization of value-in-use empirically and to determine the influence of user experience on value assessment. The third objective is the empirically comparison of mobile LBS' value-in-use in inner cities for different shopping patterns. The fourth objective is to empirically evaluate the adequacy of relevant transmitted offers as a possibility to manage the mobile LBS' value-in-use. The final objective is the derivation of managerial implications for the application and management of mobile LBS in inner cities.

This study contributes to the existing research on mobile LBS' value-in-use in multiple ways. While existing research on customers' evaluation of mobile LBS has argued from the goods-dominant perspective, we consider value assessments through the service-dominant lens, which we believe makes a valuable contribution to LBS research. Beyond this, to the best of our knowledge, this study considers shopping patterns, identified based on the assumption of goal theory, as a possible context factor of value-in-use for the first time. Additionally, by including user experience as a moderating variable, a dynamic understanding of value provides additional insights concerning the temporally dynamic nature of value-in-use, which is proposed by Helkkula et al. (2012b).

The results of our study illustrate the equal importance of utilitarian and hedonic aspects in the evaluation of mobile LBS' value-in-use during inner-city visits. Thus, our results indicate that in addition to the functional aspects, the discussion and development of mobile LBS need to consider stronger hedonistic aspects, such as the fun benefits of mobile LBS and general digital technologies in retail. Furthermore, our results point out that value assessment depends on prior user experience. In line with the channel expansion theory (Carlson and Zmud 1994), we conclude that the potential value-in-use of mobile LBS usage increases with higher user experience, which can be explained by the rising user competence and the resulting increased perception of the channel's richness. Regarding the context-dependency of value-in-use, the results indicate that all examined value-in-use components influence value-in-use regardless of shopping pattern. In addition to the similarities between value-in-use evaluations within individual shopping patterns, differences can be found regarding the most relevant value-in-use components of a specific shopping pattern. Consequently, shopping patterns might not be a fully discriminating context factor of value-in-use, and the presented value-in-use conceptualization is, to a certain degree, generalizable across multiple shopping patterns.

Our study also demonstrates that the different effects of monetary and non-monetary offers, as highlighted in sales promotion research (e.g., Buil et al. 2013; Reid et al. 2015; Büttner et al. 2014; Yi and Yoo 2011; Chandon et al. 2000), are applicable to the context of value-in-use, whereby monetary offers have a stronger effect than non-monetary offers. Moreover, our results point out that the number and type of customer-relevant offers only affect overall value-in-use through positive value-in-use components and do not influence irritation as a negative component. Therefore, the number of relevant monetary offers influences overall value-in-use through utilitarian and hedonic value-in-use components. In comparison, the number of relevant non-monetary offers influences overall value-in-use only through hedonic components. These findings can be used to manage value-in-use through the information and offers delivered by mobile LBS.

Further, our study methodologically contributes to the extant literature by using data collected from actual users immediately after its actual use and during several service events in a field study. Particularly in the context of mobile services, field studies offer various advantages over laboratory experiments if overall acceptability and influence factors, such as the impact of system functions and usage contexts, are the object of investigation (Kjeldskov and Stage 2004; Van Elzakker et al. 2008; Christensen et al. 2011; Sun and May 2013). Moreover, with the analysis of value-in-use over several service events, the boundaries of the analysis of single, static service experiences can be overcome to reveal dynamic relationships between past and present value assessments, which can lead to multifaceted contributions. Furthermore, our study contributes to the value-in-use and mobile LBS research fields by using a mixed-methods approach that combines partial least squares structural equation modeling (PLS-SEM) and fuzzy-set qualitative comparative analysis (fsQCA) to analyze the data. Therefore, the fsQCA supports and extends the knowledge gained by the PLS-SEM, which is usually used in this research field, by enabling a deeper understanding of the complex, asymmetric, and synergistic combinations of different value components. Thus, the applied mixed-methods approach makes a relevant contribution to the research on the perception of mobile LBS and provides a more comprehensive view of mobile LBS' value-in-use during shopping trips with different shopping patterns and user experiences.

The paper is structured as follows: Based on a brief overview of existing research regarding value-in-use and mobile LBS, we develop a conceptualization of mobile LBS' value-in-use in inner cities. Within this discussion, the temporally dynamic nature of value-in-use is emphasized, and the assumed moderation by customers' user experience is argued. This is followed by an identification of relevant shopping patterns as a possible context-specific factor of value-in-use evaluations based on existing literature. The number and type of transmitted offers are then discussed as a possible value driver. Afterward, the results of our empirical study are presented. The paper concludes with a discussion of our results and their managerial implications, followed by the study's limitations and suggestions for future research.

2 Conceptual Background

2.1 Mobile Location-Based Services and Value-in-Use

Mobile LBS are common tools used to link customers' real experiences with retailers and their digital experiences with their mobile devices (Faulds et al. 2018; Kang et al. 2015), thereby enabling physical retailers to extend their communication channels (McKiou and Sankisa 2011). They support customers with tailored, customized, and location-based functionalities using their location information. Mobile LBS allow customers to receive up-to-date information about their surroundings, supporting their real-time decision-making processes (Chin and Siau 2012). Consequently, they offer benefits for both users and businesses (Smith 2014). In inner cities, mobile LBS are used to provide relevant information about inner-city events and attractions. Additionally, they can transmit location-based information about inner-city retailers and service providers and current offers, thereby offering possibilities for different sales promotions. Due to the potential of mobile LBS for companies and retailing, previous research has investigated the adoption and usage of mobile LBS. Against this backdrop, different models have been introduced to explain customers' adoption intentions, focusing on innovation adoption theories such as the Technology Acceptance Model (TAM) (e.g., Choi 2018; Mao and Zhang 2014; Lee et al. 2009) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (e.g., Yun et al. 2013, 2011; Zhou 2012; Gupta et al. 2011; Xu and Gupta 2009). In addition to the drivers of mobile LBS adoption, previous research has examined barriers to LBS adoption (e.g., Kummer et al. 2018; Limpf and Voorveld 2015; Mao and Zhang 2014; Keith et al. 2012; Zhao et al. 2012; Zhou 2012; Gerpott and Berg 2011; Pee 2011; Lee et al. 2009; Xu et al. 2009a, 2005; Junglas et al. 2008).

Several scholars have suggested that mobile LBS usage is driven not by technology, but by value (Pura 2005; Lehrer et al. 2010; Constantiou et al. 2014). This suggests that research should consider not only technology utilities but also other aspects, such as emotional, psychological, or social factors (Wang et al. 2013). Against this backdrop, several studies have examined users' evaluation of mobile LBS, highlighting that LBS use is based on how valuable the user perceives the provided content to be within a particular context of use (Pura 2005). Therefore, some scholars have integrated the concept of value into their models (e.g., Pura 2005; Pee 2011; Zhang and Mao 2012, 2013). Pura (2005) introduced the first value model in the LBS context, examining six dimensions of perceived value and their effect on commitment and intention to use LBS (Pura 2005). Based on the consumption value theory, the author identified convenience value (ease and speed of achieving a task effectively and conveniently), monetary value (good value for money), emotional value (play or fun), social value (social approval and enhancement of self-image among other individuals), conditional value (circumstances that impact choice), and epistemic value (curiosity, novelty, or gained knowledge) as relevant dimensions whereby the influence of social and epistemic value could not be verified (Pura 2005). In the same vein, Pee (2011) combined the theory of consumption values and the privacy calculus model to examine intention to use mobile LBS Facebook©Places. Her study showed that not only do conditional, emotional, epistemic, functional, and social values exert a significantly positive effect on intention to use, but conditional, functional, and social values also attenuate the negative impact of perceived privacy risk on individuals' intention to use mobile LBS (Pee 2011).

In location-based advertising (LBA) research, the concept of advertising value based on Ducoffe (1995), which has been established in advertising research, is used to understand what makes mobile advertising valuable to recipients (e.g., Lin et al. 2013; Richard and Meuli 2013; Xu et al. 2009b). In this sense, LBA is viewed as a subgroup of LBS that relies on personalized information about a mobile device's position in order "(...) to personalise marketing communication with target customers" (Shieh et al. 2019, p. 380). Ducoffe (1996) identifies informativeness (providing resourceful and helpful information), irritation (being annoying or confusing), and entertainment (being fun, enjoyable, and entertaining) as core antecedents of advertising value (Ducoffe 1996). In 2014, Kim and Han introduced incentives as an additional antecedent of advertising value in the Ducoffe model. Incentives impact a customer's intention to receive mobile advertisements and agreement to receive ads when specific financial rewards are offered. Similarly, research focusing on (location-based) mobile couponing highlights the impact of economic benefits on intended redemption as well as attitudes toward mobile couponing (e.g., Achadinha et al. 2014; Dickinger and Kleijnen 2008).

However, the studies presented above view LBS and LBA as a "product" to be distributed to users, which is in line with goods-dominant logic. In this view, the user is primarily passive and solely evaluates the proposed offer of LBS. However, this view is inadequate in the context of LBS, in which customers are free to make app-related choices (Jung 2014). Instead, value is constructed through customers' experiences during usage, thereby creating value-in-use for themselves (Grönroos and Voima 2013). Therefore, the customer actively creates value through resource integration while combining resources that the service provider supplies with other resources and capabilities to create value (Vargo and Lusch 2016; Lusch and Vargo 2018; Grönroos and Voima 2013). For example, LBS offer the opportunity to receive specific information that the customer can use to achieve particular goals. Subsequently, service providers cannot create or deliver value independently (Vargo and Lusch 2008). They can offer value propositions to customers (Vargo and Lusch 2008), thereby facilitating value for them by creating potential value that the customer can transform into value-in-use (Grönroos and Voima 2013). Consequently, value-in-use is created through the integration of LBS into customers' personal processes (Bruns and Jacob 2014). Context (social, physical, temporal, and/or spatial) determines value-in-use, which is created during a dynamic and experiential process of usage as a function of past, present, and envisioned future experiences (Grönroos and Voima 2013; Helkkula et al. 2012a, b). Accordingly, value-in-use refers to the degree to which customers believe that they are better or worse off from their consumption experiences (Grönroos and Voima 2013), and "value creation becomes a structured process in which firms and customers have defined roles and goals" (Grönroos and Voima 2013, p. 138). Consequently, value-in-use integrates a trade-off between benefits and sacrifices, which are perceived within the scope of achieving context-specific customer goals in the usage process (Sweeney et al. 2018; Macdonald et al. 2016). Value-in-use is defined as "all customer-perceived consequences arising from a solution that facilitate or hinder the achievement of the customer's goals" (Macdonald et al. 2016, p. 98). Accordingly, characteristic attributes of value-in-use are customers' active role in value creation and their goals' central meaning (Hendricks 2018). Therefore, value-in-use can be understood only through knowledge of a customer's goals (Hartwig and Jacob 2018).

2.2 Conceptualization of Mobile Location-Based Services' Value-in-Use in Inner Cities

Although value-in-use conceptualizations regarding smartphone and app usage are available (e.g., Fang 2019; Lei et al. 2019; Bruns and Jacob 2016; Hartwig and Jacob 2018; Asche and Kreis 2014), there is no generally accepted conceptualization of value-in-use (Leroi-Werelds 2019; Hartwig and Jacob 2018; Sweeney et al. 2018; Heinonen et al. 2010). Therefore, no conceptualization of value-in-use concerning mobile LBS in inner cities exists either. Potential value-in-use components are discussed below, and, for this purpose, illustrated multi-dimensional value models are used, whereby established components are transformed into the usage-process context (Macdonald et al. 2016; Bruns and Jacob 2014). The value-in-use conceptualization is based on the fact that needs arising from the use process during inner-city visits are essential to customers' evaluations. Thus, the decision to use mobile LBS must be made before the actual use. Accordingly, the value-in-use components should not represent knock-out criteria for the first use.

Research has shown that privacy concerns have a negative influence on a customer's intention to download a mobile app (Tang et al. 2019; Klumpe et al. 2018; Wottrich et al. 2018; Gu et al. 2017), which is why we assume that privacy concerns are such a knock-out criterion of use. Therefore, we conclude that privacy concerns are not a component of value-in-use, but rather an upstream construct that affects the customer's initial decision to use the app for the first time. Findings on the so-called privacy paradox (for an overview, see Gerber et al. 2018), "which describes the dichotomy of information privacy attitude and actual information privacy behavior" (Gerber et al. 2018, p. 226), also support the decision to exclude privacy concerns as a value-in-use component. Privacy concerns represent something that is diffuse for people; it is not directly reflected in their actual behavior and is postponed particularly for expected short-term benefits (Wottrich et al. 2018).

Based on the extant LBS literature and the value models discussed above, the positive utilitarian components of monetary, support, and convenience benefits; the positive hedonic components of fun, social, and epistemic benefits; and the negative component of irritation have been identified as relevant customer-perceived value-in-use components.

Monetary Benefits As stated above, perceived usefulness is a core variable in technology-driven research on LBS usage. Thus, this study expresses perceived usefulness as a benefit of saving money due to redeeming sales promotions, such as mobile coupons and other incentives, provided through LBS. These financial benefits positively affect consumers' evaluation of mobile coupons (Achadinha et al. 2014; Dickinger and Kleijnen 2008), and customers perceive ads with incentives as valuable (Kim and Han 2014). "Taking advantage of a good price deal" is the main objective in the use of location-based coupons (Audrain-Pontevia et al. 2013, p. 446). As inner-city retailers and service providers' transmission of LBA messages is an essential function of mobile inner-city LBS, it can be assumed that deriving discounts and special offers is an essential objective of LBS usage. For this reason, monetary benefits are identified as a relevant value-in-use component. Here, *monetary benefits* are defined as financial benefits that the customer receives by using LBS during inner-city visits. Thus, savings from using LBS increase customer-perceived value-in-use.

Support Benefits A more general view of perceived usefulness in the LBS context is their benefits that arise through provided relevant information. Lin et al. (2013) showed that a contextual offer, which is defined as "providing consumers with interesting information related to their locations by correct location and time in order to enhance value of service" (Lin et al. 2013, p. 644), exerts the strongest impact on potential consumer attitudes toward LBS and, therefore, usage intentions (Lin et al. 2013). Additionally, regarding advertising messages, informativeness is a relevant value driver (Martins et al. 2019; Kim and Han 2014; Richard and Meuli 2013; Xu et al. 2009b; Ducoffe 1995, 1996). In addition to inner-city retailers and resident service providers' transmission of advertising messages with monetary incentives, mobile inner-city LBS can provide other information to customers that can be used to achieve customers' goals during inner-city visits more effectively. Due to personalization of this information based on customers' locations, it can be assumed that receiving this information is of particular relevance for customers and supports their realization of individualized goals during specific inner-city visits. If a customer perceives received information as useful and relevant, this will have a positive effect on their assessment of the use of mobile LBS, which is why *support benefits* are considered another value-in-use component.

Convenience Benefits Service convenience is a widely discussed construct in the marketing and service literature (e.g., Klaus and Zaichkowsky 2020; Kabadayi et al. 2019; Collier and Kimes 2013; Ding et al. 2011; Collier and Sherrell 2010; Farquhar and Rowley 2009; Seiders et al. 2007; Berry et al. 2002). Due to the increasing convenience orientation of customers, they are more likely to reflect on what they invest their time and efforts in (Seiders et al. 2007) and aim to improve their overall well-being (Roy et al. 2020). Convenience also plays an essential role in the shopping context (Bednarz and Ponder 2010), and its importance has been demonstrated both in online shopping (e.g., Jiang et al. 2013) and inner-city visits (e.g., Reimers and Chao 2014). Pura (2005) defines the convenience value of LBS as the "ease and speed of achieving a task effectively and conveniently" (Pura 2005, p. 516) and allocates its relevance to intention to use LBS (Pura 2005). Therefore, another goal of using mobile inner-city LBS is to simplify inner-city visits. If using LBS allows for faster and more convenient achievement of goals during an inner-city visit, it is likely to improve assessments of LBS usage. Thus, *convenience benefits*, as a value-in-use component, are integrated into the model.

Fun Benefits In addition to the more utilitarian goals associated with using mobile LBS in inner cities, hedonistic purposes should be considered (e.g., Yoon et al. 2018). Without considering immaterial and emotional benefits, distortions will exist in the interpretation of consumption activities, as an essential part of customer evaluation are ignored if only functional and rational aspects are included (Babin et al. 1994). According to Sheth et al. (1991), value can arise from aroused feelings or affective states and is measured on a profile of feelings, including the fun, entertainment, or pleasure associated with a service (Sheth et al. 1991). Previous studies have highlighted the positive impact of emotional value on intention to use LBS (e.g., Zhang and Mao 2012, 2013; Pee 2011; Pura 2005). Using LBS can satisfy customers' emotional need for fun. If using mobile LBS makes inner-city visits more enjoyable for customers, it can be assumed that they are perceived as valuable. Thus, the *fun benefits* of using mobile inner-city LBS are identified as another value-in-use component.

Social Benefits Sweeney and Soutar (2001) define social value as "the utility derived from the product's ability to enhance social self-concept" (Sweeney and Soutar 2001, p. 211). It is similar to the concepts of social influence and social norms, which have been investigated in technology-driven research (e.g., Mao and Zhang 2014; Yun et al. 2013, 2011; Zhou 2012). As mobile LBS in inner cities are new services, their usage can strengthen customers' self-image by making them feel like smart shoppers, and they might radiate this feeling toward others. Thus, using LBS leads to positive social consequences with other people, which can positively affect customers' assessment of LBS use. Against this backdrop, *social benefits* are conceptualized as another value-in-use component.

Epistemic Benefits According to Sheth et al. (1991), arousing curiosity and novelty, as well as satisfying a desire for knowledge, can lead to epistemic value (Sheth et al. 1991). Against this backdrop, epistemic value's influence on LBS use can be demonstrated (e.g., Zhang and Mao 2012, 2013; Pee 2011). Based on information that they receive through mobile LBS during inner-city visits, a customer has the opportunity to learn about (new) stores and restaurants, as well as service providers and leisure offers, or to be surprised and inspired by certain offers that LBS provide. This information can help the customer satisfy their curiosity, experience novelties, or acquire additional knowledge during their inner-city visits. Thus, it can be assumed that using mobile LBS can provide epistemic benefits during inner-city visits, which is why *epistemic benefits* are another component of value-in-use.

Irritation Notably, mobile LBS messages are likely to interrupt a customer's activities; for instance, they need to disrupt their goal achievement (Edwards et al.

2002). If a customer finds advertising messages to be irritating or annoying, this leads to negative feelings toward the advertisement (Yang et al. 2013) and reduces perceived advertising value (Ducoffe 1995, 1996). Several studies have investigated irritation's negative effects on advertising value and attitudes toward mobile ads (e.g., Ozcelik and Varnali 2019; Lin and Bautista 2020; Martins et al. 2019; Lin et al. 2013; Richard and Meuli 2013; Xu et al. 2009b). They found that using mobile LBS during inner-city visits can hinder the achievement of customers' individual goals. For example, obtaining an exciting offer through mobile inner-city LBS can distract a customer from his or her actual plans and disrupt their planned tasks. As a result, the inner-city visit must be extended or individual, and previously set goals cannot be reached at all, which can lead to negative emotions, such as frustration. Additionally, constantly checking one's smartphone can disturb an inner-city visit, eliciting negative customer perceptions. For this reason, *irritation* is included in this study as a value-in-use component.

As mentioned above, value-in-use is determined by the social, physical, temporal, and spatial contexts during use; therefore, it is created during the dynamic and experiential process of usage as a function of past, present, and envisioned future experiences (Grönroos and Voima 2013; Helkkula et al. 2012a, b). Against this backdrop, a temporally dynamic understanding of mobile LBS' value-in-use based on prior user experience seems to be appropriate. Evidence has been found, particularly in technology acceptance research, that previous user experiences have a moderating effect on the evaluation and use of mobile apps (e.g., Hart and Sutcliffe 2019; Newman et al. 2018; Workman 2014). Furthermore, a longitudinal study conducted by McLean et al. (2020) demonstrated that the drivers of attitudes toward the m-commerce app, which include the constructs of perceived ease of use, perceived usefulness, subjective norms, enjoyment, and customization, have different impacts in the initial adoption phase and the usage phase. Helkkula et al. (2012a) point out that in value research, value is constructed based on past, current, and expected future experiences, referring to findings on the hermeneutic circle, which states that sense-making and understanding are based on already existing knowledge, and the experience is therefore cumulative (Helkkula et al. 2012a, b; Heidegger 1962).

Moreover, as mobile LBS can also be seen as a channel that enables communication between companies and consumers, Carlson and Zmud's (1994) findings on channel expansion theory are relevant in the present context. According to channel expansion theory, experience is a central factor in the perception of a channel's richness. Therefore, understanding of a competent channel use increases with increased user experience, which leads to an increased perception of the channel's richness over time (Carlson and Zmud 1999). Moreover, the efficiency with which rich messages are encoded and decoded on a channel increases with increased experience, which is why the potential benefit of a channel also increases (Carlson and Zmud 1999). In light of the mentioned previous research and findings, it can be assumed that the value-in-use of mobile LBS is not static but varies at different service events, since the competent use of mobile LBS functions increases with increased user experience. Thus, regarding the call of Helkkula et al. (2012b) to conduct longitudinal studies on the value at several service events in order to better understand the temporal nature of that value, the moderating influence of user experience on the relationship between value-in-use and its components will be investigated.

2.3 Shopping Patterns as a Usage Context of Mobile Location-Based Services in Inner Cities

Value-in-use is assumed to depend on various contextual factors (situational, social, physical, temporal, and spatial factors) in the usage process, which can influence a customer's evaluation of a service (Grönroos and Voima 2013). One relevant context factor for the value-in-use of mobile LBS in inner cities could be customers' shopping patterns. Within this paper's scope, shopping patterns are understood as specific combinations of activities along the customer's journey during an inner-city visit. They are not tied to a customer type; in other words, customers can demonstrate different shopping patterns during various inner-city visits, depending on their shopping goals. Accordingly, shopping patterns are based on different shopping goals. Therefore, the evaluation of mobile LBS usage in inner cities could vary depending on which shopping pattern is used, and thus, what shopping goal is sought. Goal theory provides a promising basis on which to identify different shopping patterns and the shopping goals that underlie them. As already mentioned in Macdonald et al. (2011), goal theory provides important implications for customer value assessment by highlighting that value assessment takes place at multiple levels. The authors point out "that in order to effectively elicit a customer's assessment of value-in-use, customer perceptions need to be measured up as well as down the hierarchy of customer goals" (Macdonald et al. 2011, p. 674). Goal theory has also been applied by Harris et al. (2018) to examine multichannel shopping behaviors and understand multichannel shopper-journey configurations. According to goal theory, customers have a hierarchical goal system comprising higher-level, more enduring, lower-level, situational, and contextualized goals (Harris et al. 2018; Kopetz et al. 2012). One part of this hierarchical goal system is shopping motivations, which represent more abstract higher-level goals that function as an aggregation of different, more specific goals (Harris et al. 2018).

Shopping motivations are a core construct used in shopping behavior research to determine why people shop the way they do (e.g., Stone 1954; Tauber 1972; Boone et al. 1974; Bellenger and Korgaonkar 1980; Westbrook and Black 1985; Babin et al. 1994; Arnold and Reynolds 2003; Kim 2006). Although no generally accepted taxonomy of shopping motivations exists in the extant literature, researchers agree that shopping motivations can be differentiated into *hedonic* and *utilitarian* motivations (e.g., Babin et al. 1994; Childers et al. 2001; Kim 2006). Hedonic shopping motivations are those in which customers shop to seek value based on pleasure, recreational consumption, and high-arousal stimuli. Conversely, utilitarian shopping motivations are more efficient and rational, involving shopping with an emphasis on task completion (Hirschman and Holbrook 1982; Babin et al. 1994; Scarpi 2006). Arnold and Reynolds (2003) developed a widely accepted taxonomy of hedonistic shopping motivations. As part of their qualitative study, the authors identified hedonic shopping motivations as adventure shopping (stimulation, adventure), social shopping (sharing leisure time with friends and family and socializing with others), gratification shopping (self-gratification and stress reduction), idea shopping (searching for new trends, products, and innovations), role shopping (satisfaction through shopping for others), and value shopping (discovery of special offers, discounts, and bargain hunting) (Arnold and Reynolds 2003). Based on this taxonomy, Kim (2006) investigated hedonic and utilitarian motivations behind inner-city shopping, extending the classification by two utilitarian shopping motivations: efficiency and achievement. Within this framework, *efficiency* defines the need for customers to save time and resources, while *achievement* refers to the goal-driven orientation of finding specific products that were sought at the beginning of the shopping trip (Kim 2006). Her findings suggest that inner-city shoppers have higher hedonic shopping motivations than non-inner-city shoppers (Kim 2006).

In line with goal theory, it can be assumed that various shopping motives drive different shopping patterns as higher-level goals and that these shopping patterns are associated with more specific shopping-related goals that serve as focal goals. Even though the goals underlying shopping patterns are diverse, elementary combinations can be derived in which inner-city visits can be classified. Against this backdrop, the shopping motives of adventure shopping, gratification shopping, and idea shopping are combined into the shopping pattern of *experience shopping*, as they are all related to recreational activities and serve the focal goal of shaping personal pleasure. The shopping motives of role shopping and achievement are summed up under task-related goals. However, shopping tasks can be very different, which explains why a further distinction is made between situation-specific shopping and habitual shopping. *Situation-specific shopping* is based on the shopping task's focal goal tied to a situational need, such as shopping for a specific occasion or the unscheduled replacement of a defective item. On the other hand, *habitual shopping* is based on the focal goal of making individual routine purchases, which are characterized by little searching and cognition, in which the customer already has experience. An example of this might be the regular replacement of fast-moving consumer goods. Utilitarian motivation efficiency is classified under the shopping pattern of *convenience shopping*, entailing shopping trips in which the customer's focal goal is to minimize time and effort. The pattern of *social shopping* is based on the focal goal of social exchanges with other people, such as friends, family, other inner-city visitors, and staff, which is why this pattern is associated with the shopping motivation of social shopping. The final shopping pattern is *bargain hunting*, which combines trips that are motivated by value shopping and those in which the customer's aim is to find good deals and strike bargains to save money. As it can be assumed that not every visit to the inner city is used for shopping and visiting stores but can also be used for other non-shopping-related activities, such as visiting leisure centers, restaurants, hairdressers, banks and doctors, a seventh pattern is considered in this study: *inner-city service usage*. Table 1 summarizes the shopping patterns mentioned here and presents customers' focal goals and underlying shopping motivations.

These shopping patterns may affect customers' assessments of using mobile LBS in inner cities due to their individual goals. Moreover, extant research concerning shopping orientations has shown that consumers with task-focused shopping orientations and those with experiential ones process information differently while shopping (Büttner et al. 2013). Additionally, it has been found that shopping orien-

Table 1 Overview of shopping patterns

Shopping pattern	Focal goal	Underlying shopping motivations as higher-level goals
Experience Shopping	Shopping to achieve shopping experiences that lead to pleasure. As a recreational activity, shopping is perceived as worthwhile in itself	Adventure Shopping Gratification Shopping Idea Shopping
Situation-Specific Shopping	Shopping to fulfil a situation-specific consumption need, such as the need for a particular piece of merchandise for a specific occasion	Achievement Role Shopping
Habitual Shopping	Shopping to fulfil a habitual consumption need that does not require much search or cognition, such as replacing fast-moving consumer goods	Achievement
Convenience Shopping	Shopping to complete shopping tasks efficiently in terms of time, with minimal effort	Efficiency
Social Shopping	Shopping for social exchanges with other people, such as friends, family, other inner-city visitors, or staff	Social Shopping
Bargain Hunting	Shopping for sales, looking for discounts, and hunting for bargains	Value Shopping
Inner-City Service Usage	Inner-city visits for all non-shopping-related activities during inner-city visits (visiting service providers, restaurants, cafes, or bars, or doing leisure activities)	Non-shopping-related Utilitarian or Hedonic Motivations

tations influence consumers' evaluations of retailer communication (Büttner et al. 2014). Thus, the information processing and effectiveness of retailer communications via LBS might also depend on shopping orientation, indicating differences between shopping patterns. These differences can be considered an additional reason to assume that shopping patterns are a context factor that affects mobile LBS' value-in-use in inner cities.

2.4 Sales Promotion as a Driver of Mobile Location-Based Services' Value-in-Use in Inner Cities

From a retailer's point of view, possibilities of positively influencing value-in-use are of particular interest. Based on the goal-directedness of the value-in-use, the content provided by mobile LBS may offer the option of influencing it. Since the transmission of offers is a central function of mobile LBS, sales promotions may be relevant content and, therefore, a chance for retailers to enhance value-in-use. Numerous studies have pointed out that sales promotions influence customer behavior and have a positive effect on, for example, purchase intention (e.g., Drechsler et al. 2017; Pacheco and Rahman 2015; Palazon and Delgado 2009; Shi et al. 2005; Laroche et al. 2003) and sales volume (e.g., Heilman et al. 2011; Shi et al. 2005; Bawa and Shoemaker 2004). Within the scope of existing research, a positive influence of the relevance of advertising messages on the perceived value of LBA has been demonstrated (e.g., Hühn et al. 2017; Chopdar and Balakrishnan 2020; Lin and Bautista 2020), which is why information regarding sales promotions may represent a driver of value assessment. Based on the assumption that the number of available relevant offers determines the content quality of a mobile LBS, we assume that an increased number of transmitted relevant offers during an inner-city trip has a positive influence on the perception of the benefits (and a negative influence on the irritation) associated with their use, and thus increases the overall value-in-use.

The literature classifies sales promotions into two main types: monetary (e.g., price discounts and coupons) and non-monetary offers (e.g., free gifts, free samples, sweepstakes, and assortment information) (e.g., Büttner et al. 2014; Yi and Yoo 2011; Gedenk et al. 2010; Chandon et al. 2000). In this context, existing research on sales promotion shows that monetary and non-monetary offers differ in terms of both their effectiveness and customers' perceptions. Research on sales promotions has focused mainly on monetary promotions, whereby the relevance of non-monetary promotions is continuously increasing, and research has focused on the different effects of both types. In general, monetary promotions are more efficient in the short term than non-monetary promotions (e.g., Alvarez and Casielles 2005; Gilbert and Jackaria 2002; Chandon et al. 2000); however, they are also associated with more long-term risks (e.g., Buil et al. 2013; Yi and Yoo 2011; Mela et al. 1997). Furthermore, it has been shown that the perceived benefits of both types of promotion, which go beyond purely monetary benefits, are different. Monetary promotions are typically associated with utilitarian benefits, and non-monetary promotions are typically associated with hedonistic benefits (Sinha and Verma 2020; Reid et al. 2015; Chandon et al. 2000). Moreover, both types of sales promotions are different attractive, depending on the shopping orientation (Büttner et al. 2014). Accordingly, against the background of the previously mentioned findings on the different effects of the two sales promotion types, we will analyze the influence of both types of sales promotions on each value-in-use component and determine their differences.

3 Field Study

3.1 Sample and Data Collection

To recruit users and empirically test the actual value-in-use evaluations of a mobile LBS app in inner cities, we conducted a field test that evaluated a prototype of a location-based inner-city app[1] in a German inner city. This app includes several functions and combines various information about retailers, service providers, gastronomy, and the city's overall leisure center in one platform. The user can learn about current events occurring in the inner city on the app's home screen, access participating inner-city providers' profiles (which include photos, contact details, descriptions, and direct contact and navigation functions), and view current offers from those providers. Based on the user's gender and stated interests, the offers are prefiltered and can be sorted by relevance, proximity to the company, and release date. Participating providers and the inner city are equipped with beacons that enable

[1] The smartmarket^2-app was developed by the Chair of Business Information Systems, Paderborn University and the European Research Center for Information Systems, University of Muenster, in the context of the research project smartmarket^2 funded by the Federal Ministry of Education and Research.

location-based communication with the LBS app. As soon as the users enter those beacons' transmission range, location-based offers are triggered that include alerts about events (e.g., upcoming concerts, readings, or screenings), tourist information (e.g., sightseeing information), or sales promotions (e.g., coupons and offers). To allow for location-based communication, users can activate a shopping trip in the app, thereby allowing their location data to be recorded, and they can agree to receive push notifications for that specific trip.

We collected data from business students during a field test of the aforementioned mobile LBS app that lasted from November 1, 2018, to January 7, 2019. The students were recruited within the framework of a bachelor course and through a poster campaign on campus[2]. During an informational event, the LBS app and its functionality was presented in detail, and the data collection via the app was discussed in depth; thus, potential participants were adequately informed, particularly about the protection of their data. In order to minimize the participants' privacy concerns and increase their willingness to participate, it was decided that as little personal data as possible would be collected from them.

We recruited 298 participants, all of whom used the LBS app during the field test. Using an in-app questionnaire that was displayed right after the users ended their inner-city trips with the app and asked them to evaluate the app and provide details about their usage during their trips, we were able to collect survey data on $n = 1216$ trips. After the data cleansing[3], a data set of $n = 760$[4] evaluations of the app usage during inner-city trips across all shopping patterns was retained. The average trip duration was 1 h and 20 min, with the trip length varying between a minimum of 10 min and a maximum of 8 h and 8 min. The trips were distributed among the shopping patterns as follows: 350 experience shopping trips, 131 inner-city service usage trips, 129 situation-specific shopping trips, 54 bargain-hunting trips, 42 social shopping trips, 29 habitual shopping trips, and 25 convenience shopping trips. Fifty-nine inner-city companies participated in the field study. Among them were shops, service providers, restaurants, cafés and bars, leisure providers, and market stand operators at the local Christmas market. During the test period, a total of 132 offers were published, of which 61 were monetary and 71 were non-monetary. The 760

[2] For the course participants, participation was encouraged by a bonus system for the course's exam; for the other participants, it was encouraged by a raffle for shopping vouchers from the municipal advertising association.

[3] During the data cleansing, 313 trips were initially excluded from the sample due to technical problems. For some of the trips, entries were recorded in the database incorrectly, incompletely, or at all. An additional 10 trips had to be excluded, as their duration lasted several days, and it was not possible to assign the data to a specific inner-city visit. Furthermore, 74 trips were excluded that had been started by the same person on the same day and finished in less than an hour; here, too, no clear allocation could be made, and it was therefore not possible to conclude that technical problems had occurred during the recording. Finally, 59 trips that were either shorter than ten minutes or longer than 10 h were excluded since here, the reliability of the recorded assessments was questionable.

[4] Most of the trips began between Monday and Thursday (543 trips; 71.45%). In contrast, 101 trips (13.29%) took place on Fridays, and 116 trips (15.26%) took place on weekends. In more than 50% of the trips, the participant was accompanied by other people (448 trips; 58.95%), and approximately three-quarters of the trips (576 trips; 75.79%) were, at least in principle, planned with a purchase-oriented aim (i.e., essential products, product groups from which to buy, and/or shops to visit).

trips resulted in 919 active interactions with the offers. Active interaction denoted that an offer was actively opened by the user either from the offer list or by a push notification.

As participants were supposed to answer the in-app questionnaire right after ending their trips to the inner city, the questionnaire had to be short, easily answerable, and provide as little irritation as possible to avoid biased evaluations of the app usage. For this reason, mainly single items were used, which has been proven to be effective for questionnaires on mobile devices with limited available resources (e.g., Reichhart 2014). At the start of the questionnaire, the participants were asked how they would describe their inner-city visit in retrospect[5]. Furthermore, we used single, seven-point, Likert-scaled items for the value-in-use components, and three seven-point, Likert-scaled items for the overall value-in-use assessment, using the anchor points "totally agree" (7) and "totally disagree" (1). Table A-1 (Web Appendix, p. 1) provides an overview of the items' wording and sources.

3.2 Mobile Location-Based Services' Value-in-Use Model and the Moderation Effects of User Experience

We employed PLS-SEM to analyze the collected data. PLS-SEM combines elements from factor analysis and path analysis by estimating coefficients of measurement models (individual constructs) simultaneously, as well as structural models (relationships between various constructs) iterative in partial ordinary least squares regression models (Hair et al. 2011). PLS-SEM is a suitable method for this study because, unlike covariance-based structural equation modeling (CB-SEM), it does not require normally distributed data (Hair et al. 2017, 2019). Additionally, PLS-SEM has greater statistical power than CB-SEM (Sarstedt and Mooi 2019). Based on the concept of mobile LBS' value-in-use in inner cities presented above, a Multiple Indicators, Multiple Causes (MIMIC) structural model (e.g., Jöreskog and Goldberger 1975; Diamantopoulos and Temme 2013; Chen and Jiang 2019) was applied in this study, which, in addition to the seven value-in-use components, included a global measurement of value-in-use by means of three reflective items. Between the value-in-use components and the overall value-in-use, a formative related relationship was modeled. To analyze our data, we used the statistical software SmartPLS 3.0 (Ringle et al. 2015), a path-weighting scheme (Henseler 2010), a bootstrap procedure with 5000 replications, and a blindfolding procedure with an omission distance of 7 (Hair et al. 2011). No missing values existed, as we removed all missing data during the data cleansing procedure.

Following the procedures and guidelines used in other studies that applied PLS-SEM, we first evaluated the measurement models (Hair et al. 2017). To assess

[5] As possible answers, they were shown the items from Table 2, which operationalizes the six shopping-related patterns described above. Also, they were given the option of selecting "I did not shop and did not visit any shops." In a second step, the participants were asked whether they also visited the inner city to use services, visit restaurants, and/or participate in leisure activities. Multiple selections were possible. If the participants indicated that they did not visit the inner-city for shopping (Step 1) but only non-shopping activities (Step 2), the trip was assigned to the inner-city service usage pattern. The grouping of trips according to their shopping patterns was, therefore, based on the participants' self-disclosure.

the measurement models, we evaluated the internal consistency reliability, as well as the convergent and discriminant validity of our reflectively measured construct (Hair et al. 2019, 2012; Wong 2013). Indicator reliability regarding value-in-use, as the only multi-item construct, could be assumed, as all three indicator loadings surpassed the threshold of 0.708 (Chin 2010). Consequently, the value-in-use construct explained more than 50% of the item's variance, which was acceptable. The values for composite reliability (CR), Dijkstra-Henseler statistics (rhoA), and Cronbach's alpha (CA), as well as the corresponding bias-corrected bootstrap confidence intervals, were between the lower boundary value of 0.7 and the upper boundary value of 0.95 (Hair et al. 2019). Thus, internal consistency reliability could be assumed. We also assessed the average variance extracted (AVE) to evaluate the convergent validity of the value-in-use construct, which is the extent to which the construct explains variance in its items (e.g., Hair et al. 2017, 2019). The value-in-use construct's AVE passed the suggested minimum value of 0.5. The results of the internal consistency reliability and convergent validity assessments are shown in Table A-2 (Web Appendix, p. 2). To assess our constructs' discriminant validity, we applied the Fornell-Larcker criterion, cross-loadings, and the heterotrait-monotrait (HTMT) ratio to the correlations (e.g., Hair et al. 2017, 2019). Neither the Fornell-Larcker criterion (squared AVE = 0.977 > correlations with all other constructs = [–0.215;0.694]) nor the cross-loadings (correlations, value-in-use and its items = [0.829;0.915] > correlations with other items = [–0.215;0.718]) revealed any indications that challenged the conclusion that all constructs are empirically distinct from each other. However, as the Fornell-Larcker criterion does not perform well in PLS-SEM (Henseler et al. 2015), the HTMT criterion was also assessed. The 0.85 threshold was exceeded neither by the HTMT values nor by the upper limit of the respective corrected bootstrap confidence interval. Additionally, the confidence intervals did not include an HTMT value of 1 (Henseler et al. 2015), which is why discriminant validity could be assumed. Table A-3 (Web Appendix, p. 3) summarizes the results of the HTMT criterion assessment.

To evaluate the structural model, we assessed both the standard assessment criteria coefficient of determination (R^2) and the blindfolding-based, cross-validated redundancy measure of Stone Geisser Q^2, possible collinearity problems, and the statistical significance and relevance of the path coefficients (e.g., Hair et al. 2017, 2019). Table A-4 (Web Appendix, p. 4) sums up the results of the structural model assessment. All the exogenous variables' VIF values were near 3 or lower (Becker et al. 2015). Thus, no collinearity problems were expected. The R^2 of our model was 0.649, which is why our value-in-use model had moderate explanatory power ($0.5 \leq R^2 < 0.75$; Henseler et al. 2009; Hair et al. 2019, 2011). To assess the magnitude of the exogenous constructs' effects, we analyzed effect sizes (f^2), describing the contribution of an exogenous construct to an endogenous variable's R^2 value relative to the amount of unexplained variance (Henseler et al. 2009). Convenience benefits, fun benefits, and epistemic benefits had an f^2 above 0.02 and, therefore, a small effect size (Cohen 1988). To evaluate the model's predictive relevance, we also examined the Stone Geisser Q^2 value (Geisser 1974; Stone 1974) using a blindfolding procedure. The Q^2 value of our value-in-use model was 0.467, which is why

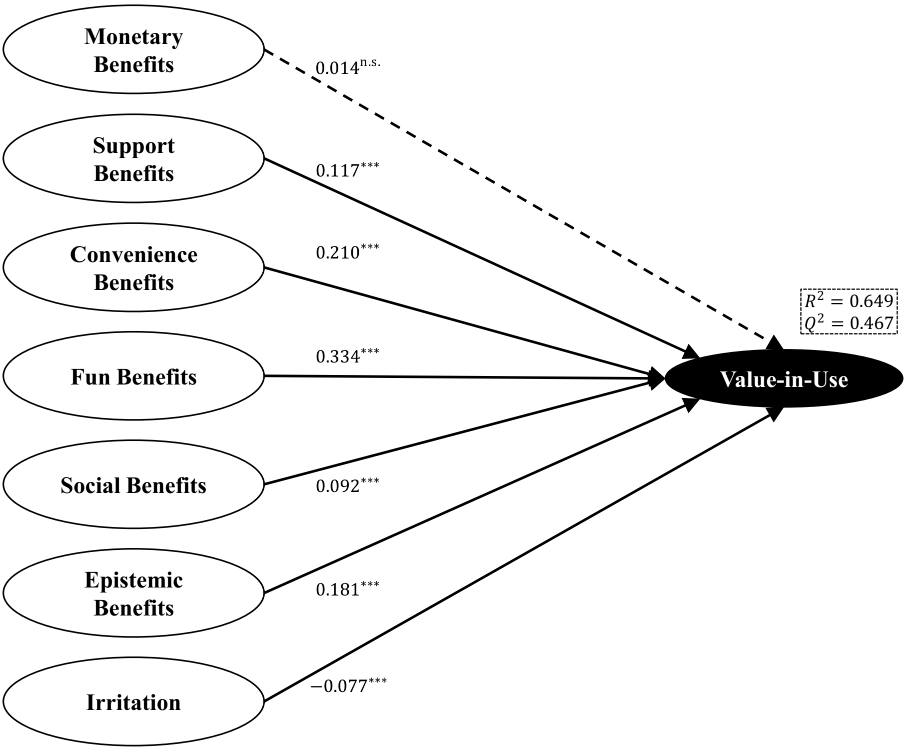

Fig. 1 Overview of the MIMIC model's results. Note: *** = $p < 1\%$; *n.s.* = not significant

our value-in-use model had medium predictive relevance ($0.25 \leq Q^2 < 0.50$; Hair et al. 2019).

Since PLS-SEM is a regression-based analysis method, whether the established model had endogeneity problems needed to be determined. If an endogeneity problem existed, the estimated path coefficients would be biased and could no longer be interpreted causally. Following Hult et al.'s (2018) guidelines, we applied Park and Gupta's (2012) Gaussian copula approach, using the latent variable scores of the SmartPLS output as input for the analysis in R-Studio[6]. We found that neither of the Gaussian copulas were significant ($p > 0.10$), as depicted in Table A-5 (Web Appendix, p. 5), which suggests that endogeneity was not present in our value-in-use model and thus was less likely to affect the results.

The model's results are visualized in Fig. 1 and show that all value-in-use components exhibited significant path coefficients ($p < 1\%$) except monetary benefits, which were not significant. Fun benefits had the highest positive path coefficient, at 0.334, followed by convenience benefits at 0.210. Epistemic benefits (0.181), support benefits (0.117), and social benefits (0.092) had the lowest positive path

[6] Our analysis draws on the R code presented in Hult et al. (2018), which can be downloaded at https://www.pls-sem.net/downloads/gaussian-copula-files/.

Table 2 Moderated value-in-use model: Results of the structural model

	Inner VIF Values	Coefficient	*p*-value	f^2
Monetary Benefits	1.972	0.025	0.423	0.001
Support Benefits	2.925	0.102**	0.014	0.010
Convenience Benefits	3.199	0.187***	0.000	0.032
Fun Benefits	2.322	0.357***	0.000	0.160
Social Benefits	1.610	0.098***	0.001	0.017
Epistemic Benefits	2.131	0.189***	0.000	0.048
Irritation	1.132	–0.070***	0.007	0.012
User Experience	1.525	0.016	0.548	0.000
User Experience X Monetary Benefits	1.670	0.067**	0.050	0.006 (small)
User Experience X Support Benefits	3.808	–0.056	0.312	0.002 (non)
User Experience X Convenience Benefits	4.478	–0.035	0.539	0.001 (non)
User Experience X Fun Benefits	3.930	0.119**	0.017	0.011 (medium)
User Experience X Social Benefits	1.797	–0.010	0.771	0.000 (non)
User Experience X Epistemic Benefits	1.647	0.000	0.994	0.000 (non)
User Experience X Irritation	1.457	0.051*	0.078	0.005 (small)
R^2	0.655 (moderate exploratory power)			
R^2 adjusted	0.648			
Q^2	0.490 (medium predictive relevance)			

coefficients. As expected, irritation had a negative path; however, compared to the other paths, it had a low path coefficient, with a value of –0.077.

Due to the temporal nature of value-in-use, the moderating effect of the user experience is examined below. Since the trip data represented longitudinal data, and several trips and evaluations were available from each user as a result, the trip number served as an approximation of the actual user experience for the respective trip and was included in the model as a continuous moderator variable. Thus, it was possible to measure the value-in-use at different service events, as suggested in Helkkula et al. (2012a, b).

The software SmartPLS 3.0 (Ringle et al. 2015) was again used for the analysis. The interaction terms were created using the two-step approach proposed by Chin et al. (2003) based on the standardized data. This approach was used due to its universal applicability and on the basis that it exhibits a higher level of statistical power (Memon et al. 2019; Hair et al. 2017; Chin et al. 2003). After modeling the moderation model, the PLS algorithm, which included a path-weighting scheme (Henseler 2010), a bootstrap procedure with 10,000 replications, and a blindfolding procedure with an omission distance of 7 (Hair et al. 2011), was applied. First, we checked the measurement model, focusing on the discriminant validity since the value-in-use measurement model was still the only multi-item construct. As shown in Tables A-6 and A-7 (Web Appendix, p. 6–8), the measurement model of the value-in-use met all thresholds. The structural model could then be analyzed. An overview of the results of the assessment of the structural model is presented in Table 2.

As in the value-in-use model without moderation, all the value-in-use components except monetary benefits were significant. A direct influence of the user experience on the value-in-use could not be confirmed. However, the results showed significant positive influences of the interaction terms User Experience X Monetary Benefits, User Experience X Fun Benefits, and User Experience X Irritation. Thus, it can be stated that the influence of the value-in-use components of monetary benefits, fun benefits, and irritation increases as user experience increases.

The R^2 of the moderation model was 0.655, which is why our value-in-use model had moderate explanatory power ($0.5 \le R^2 < 0.75$; Henseler et al. 2009; Hair et al. 2019, 2011). Compared to the value-in-use model without moderation, there was an increase in R^2 (adjusted) from 0.645 to 0.648, which showed an improvement in explanatory power and the relevance of considering the user experience's moderator variable, even if the effect is relatively small. In the moderator analyses, effect size (f^2) was of particular interest, since in the case of interaction terms, it indicates the explanatory power of the moderation for the independent construct (Memon et al. 2019; Hair et al. 2017). Due to the generally smaller average effect size in moderated models, lower thresholds were accepted, which is why a value of 0.005 was considered a small effect size, 0.01 was considered medium, and 0.25 was considered substantial (Hair et al. 2017). As summarized in Table 2, the interaction terms User Experience X Monetary Benefits and User Experience X Irritation had a small effect size, and the interaction term User Experience X Fun Benefits had a medium effect size. These results underline the relevance of the user experience as a moderating construct in the value-in-use model.

Further, we analyzed the moderating influence of the user experience on the relationships between value-in-use and monetary benefits, fun benefits, and irritation in more detail. Within this scope, we took a closer look at how the relationship between the value-in-use components and the value-in-use is affected by different manifestations of the moderator variable user experience. We also examined the significance of those manifestations of user experience to uncover regional ranges of significance. To investigate the regional significance of the conditional indirect effects, we applied Hayes' PROCESS macro version 3.4 for SPSS with model 1, including the Johnson-Neyman technique (Hayes 2018)[7]. Tables A-8, A-9, and A-10 (Web Appendix, p. 9–11) show the results for the conditional effects of monetary benefits, irritation, and fun benefits for different manifestations of the moderating variable user experience (see Column 1). Column 2 shows the path coefficients, and Column 3 the corresponding *p*-values of the respective value-in-use component. The results reveal that the moderating effect of user experience on the relationship between monetary benefits and value-in-use and on the relationship between irritation and value-in-use was not significant for all levels of user experience. Fur-

[7] To ensure comparability with the SmartPLS results, we used the latent variable scores. The value-in-use was defined as the dependent variable, and user experience was the moderator. The independent variable represented the respective value-in-use component. We included the remaining six value-in-use components as covariates in the respective models. Since PROCESS macro does not allow simultaneous estimation of the moderating effects on all relationships between the value-in-use components and the value-in-use but only on the relationship between the defined dependent and independent variable, we also considered the latent variable scores of the other six interaction terms as covariates.

thermore, the relationship between fun benefits and value-in-use was significant for all experience levels.

More precisely, the conditional effect of monetary benefits was significant only from the fourth trip onwards and then became stronger as the number of trips increased (see Table A-8, Web Appendix, p. 9). This effect is also illustrated by the simple slope diagram seen in Fig. 2. These findings helped to interpret the non-significant path coefficient of the monetary benefits in the value-in-use model without moderation. The conditional effect of irritation, however, was significant only in the first four trips (see Table A-9, Web Appendix, p. 10). The influence of irritation decreased with increasing user experience and disappears after the fourth trip. Fig. 3 illustrates this decrease using a simple slope diagram. The conditional effect of the fun benefits was significant for all experience levels (see Table A-10, Web Appendix, p. 11). This effect increased with increasing user experience (see Fig. 4).

3.3 Shopping Patterns as a Usage Context of Mobile Location-Based Services

3.3.1 Appropriateness of Using Fuzzy-Set Qualitative Comparative Analysis and Data Calibration

To gain a deeper understanding of whether customers exhibiting different shopping patterns differ in their evaluation of mobile LBS, the current study employed fsQCA, which has recently been applied in several business contexts (e.g., Wünderlich and Hogreve 2019; see Wagemann et al. 2016 for a review). The use of fsQCA alongside other quantitative methods has been shown to complement and supplement scientific results regarding general marketing-related topics (e.g., Frösén et al. 2016), as well as mobile apps (Picoto et al. 2019; Verissimo 2018) and smart technologies in retail (Roy et al. 2018).

FsQCA is a set-theoretic method used to uncover how different combinations of variables (termed conditions; here: value-in-use components) contribute to a target variable (termed outcomes; here: value-in-use) (e.g., Fiss 2007). Based on Boolean algebra and algorithms, fsQCA reduces the complex combinations of variables into a "reduced set of configurations that lead to the outcome" (Fiss 2011, p. 402). In short, fsQCA allows for multiple, equifinal solutions that all lead to the same outcome (e.g., Wagemann et al. 2016). Thus, in this study, fsQCA enabled us to analyze in detail to what extent different combinations of the perception of value-in-use components lead to high or low mobile LBS' value-in-use during trips differentiated by shopping patterns. Furthermore, fsQCA incorporates causal asymmetry, which means that different (combinations of) conditions can explain outcomes and their negation (e.g., Schneider and Wagemann 2012, p. 6). Therefore, it is not possible to infer the explanation of the absence of an outcome (i.e., a negation) by examining the explanation of that outcome (i.e., the conditions or combination of conditions leading to high value-in-use are different from those that lead to the absence of a high value-in-use). These features demonstrate why fsQCA was a suitable method for the present research goal, as it was able to uncover which combinations of value-in-use components lead to high mobile LBS' value-in-use (or low value-

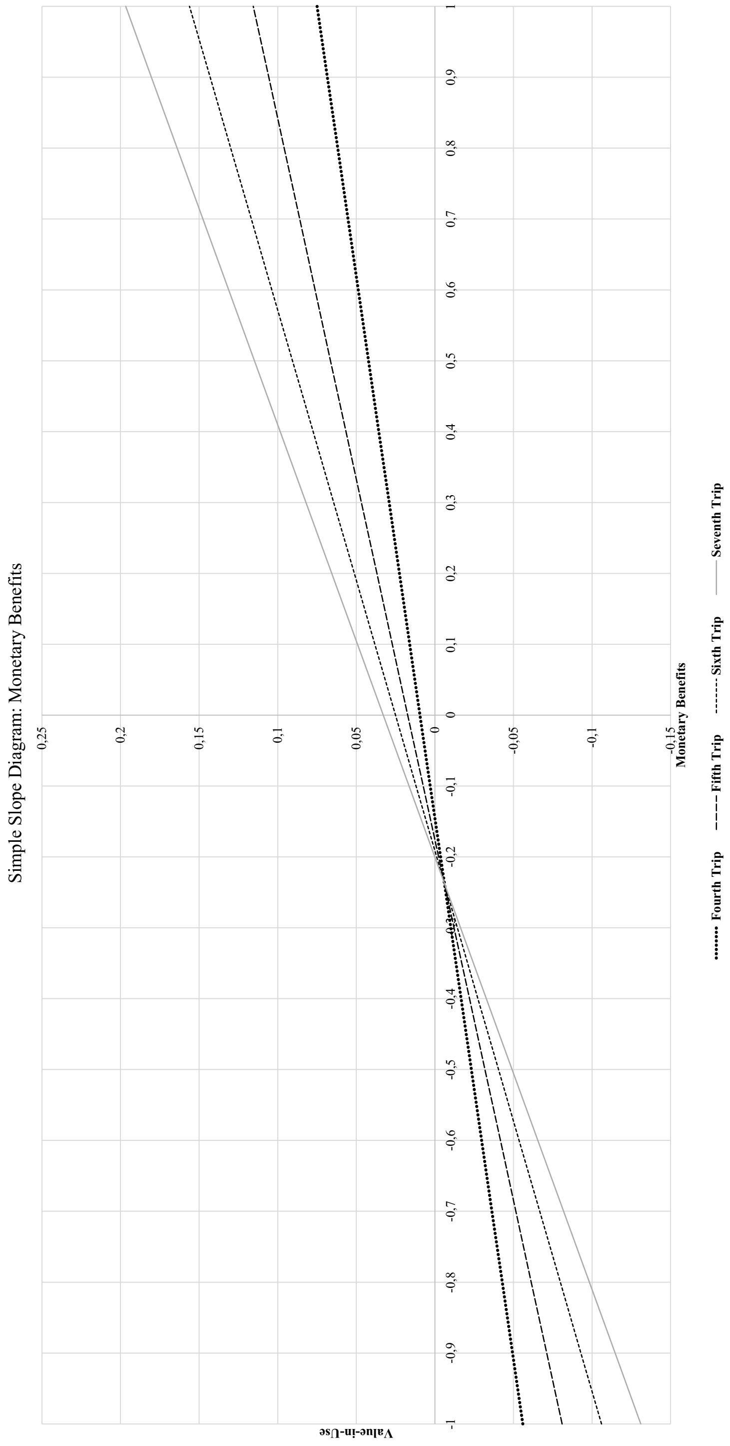

Fig. 2 Monetary benefits: A simple slope diagram. *Note:* Due to the low frequency of more than seven completed trips, only the first seven significant trips are presented here

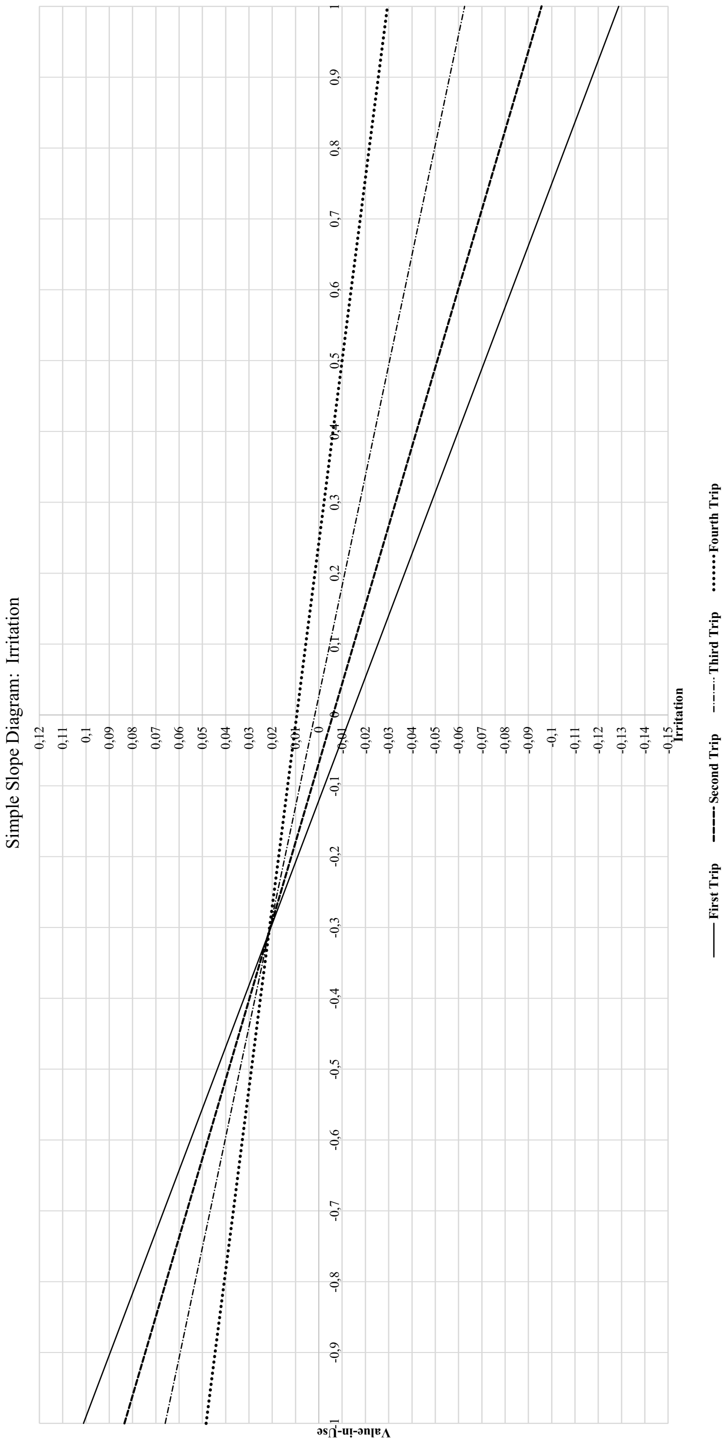

Fig. 3 Irritation: A simple slope diagram. *Note:* Due to the low frequency of more than seven completed trips, only the first seven significant trips are presented here

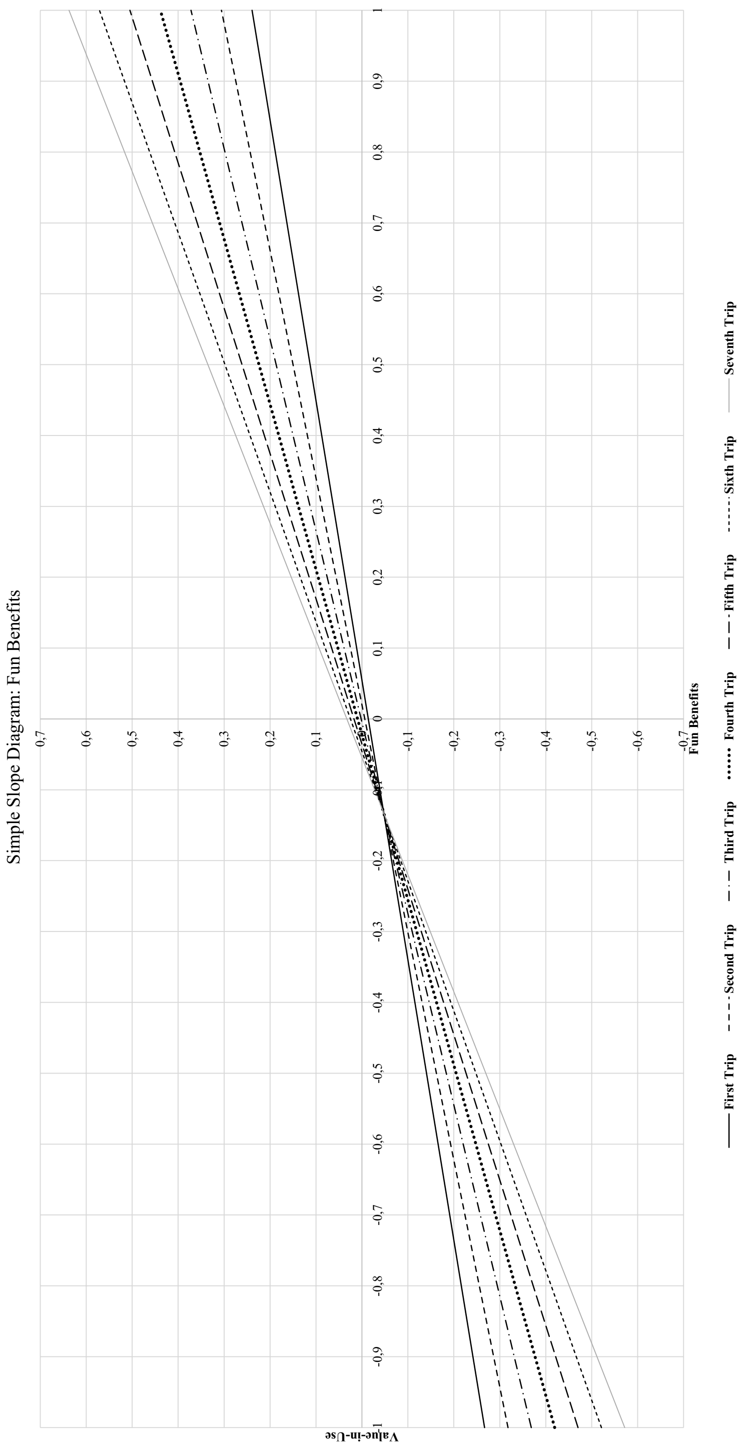

Fig. 4 Fun benefits: A simple slope diagram. *Note:* Due to the low frequency of more than seven completed trips, only the first seven significant trips are presented here

in-use) in inner cities. The fsQCA results found here regarding different shopping patterns can be used to develop more in-depth insights into different combinations of perceived value-in-use components within the respective shopping patterns, which entail the perception of high or low value-in-use. These results can complement and supplement the PLS-SEM results, as fsQCA does not exhibit the same limitations as other quantitative methods (e.g. Frösén et al. 2016).

Based on the limited number of observations (cases in QCA terminology) made in this study, we excluded the following shopping patterns, each of which had fewer than 50 cases, from the analysis: convenience shopping ($n=25$); habitual shopping ($n=29$); and social shopping ($n=42$). The reasoning behind this decision was based on research by Marx (2010) and Marx and Dusa (2011), who demonstrated that a relatively low number of cases in conjunction with a relatively high number of conditions leads to seemingly feasible results on random data. All excluded shopping patterns met those unfavorable conditions; thus, if they had been used in this study, they would also have led to high limited (empirical) diversity (Ragin 2000; Schneider and Wagemann 2012), possibly distorting the results. Therefore, we retained the following four shopping patterns to be analyzed: experience shopping ($n=350$); situation-specific shopping ($n=129$); bargain hunting ($n=54$) and inner-city service usage ($n=131$). The study followed generally accepted fsQCA procedures (e.g., Wagemann et al. 2016; Schneider and Wagemann 2012; Fiss 2011; Ragin 2000) based on fsQCA 3.0 software (Ragin and Davey 2016). The calibration of the measures was the basis of the analysis. We used the direct method of calibration (Ragin 2008) to transform our Likert-scale items into fuzzy sets that ranged from 0 (no set membership) to 1 (full set membership). For the single items, the item value "7" represented the anchor value 0.95, and "1" represented the anchor value for the 0.05 threshold. We set the anchor for the crossover point at 0.5 for set membership at the non-existent item value of 3.9 and not—as other studies have done—at 4. The reason for this is that assigning the fuzzy value of 0.5 to existing values should be avoided (Wagemann et al. 2016). Therefore, we decided to assign a non-existent value; in other words, all cases with an item value of "4" on any of the single items were barely in the set of a positive condition evaluation. For the calibration of the "value-in-use" outcome, we formed an additive index for the three value-in-use items and assigned the anchor points for 0.95 at 19 (and above), 0.5 at 11.5, and 0.05 at 5 and below. The next step in the analysis was the identification of necessary conditions, followed by the identification of sufficient conditions.

3.3.2 Identification of Necessary Conditions

The next step in the analysis was to check for necessary conditions for the target variable (e.g., Schneider and Wagemann 2012; Ragin 2000); this was done for both high value-in-use and its negation (low value-in-use, denoted as ~value). The results of this analysis can be found in Tables 3 and 4. For high value-in-use, only two conditions surpassed the lowest advisable consistency threshold of 0.9 for necessary conditions (Ragin 2006): low irritation (denoted as ~irritation) for situation-specific shopping and "fun" for bargain hunting. For the negation of the outcome, we observed a low monetary value (~monetary) surpassing the threshold for all shop-

Table 3 Results of the evaluation of necessary conditions and high value-in-use

Conditions	Experience Shopping		Situation-Specific Shopping		Bargain Hunting		Inner-City Service Usage	
	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage
Monetary	0.5105	0.8422	0.3923	0.8776	0.6869	0.8899	0.5263	0.7738
~Monetary	0.7472	0.4974	0.8117	0.4816	0.5742	0.4997	0.7132	0.3923
Support	0.7549	0.8340	0.6428	0.8625	0.7773	0.8868	0.6930	0.7649
~Support	0.5719	0.4753	0.6525	0.4703	0.5414	0.5184	0.5912	0.3713
Convenience	0.6434	0.8731	0.6214	0.9051	0.7737	0.9793	0.6848	0.8893
~Convenience	0.6631	0.4835	0.6699	0.4632	0.5457	0.4825	0.6432	0.3722
Fun	0.8520	0.7819	0.8527	0.8156	**0.9082**	**0.8393**	0.8900	0.7260
~Fun	0.4917	0.4826	0.5288	0.4865	0.4265	0.5085	0.4744	0.3729
Epistemic	0.7520	0.8087	0.6950	0.8149	0.7762	0.8215	0.7298	0.7993
~Epistemic	0.5550	0.4709	0.6105	0.4771	0.5123	0.5248	0.5913	0.3731
Social	0.6264	0.8358	0.5285	0.8455	0.7108	0.8691	0.6852	0.7427
~Social	0.6672	0.4910	0.7393	0.4904	0.5560	0.5040	0.6255	0.3970
Irritation	0.4068	0.6088	0.3837	0.5852	0.4080	0.7241	0.4617	0.5467
~Irritation	0.8852	0.6146	**0.9162**	**0.6203**	0.8719	0.6423	0.8604	0.5203

Table 4 Results of the evaluation of necessary conditions and low value-in-use

Conditions	Experience Shopping		Situation-Specific Shopping		Bargain Hunting		Inner-City Service Usage	
	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage
Monetary	0.3189	0.5830	0.2284	0.5788	0.3758	0.4484	0.2626	0.5784
~Monetary	**0.9137**	**0.6742**	**0.9517**	**0.6395**	**0.9077**	**0.7276**	0.8973	0.7394
Support	0.4304	0.5271	0.3512	0.5337	0.4538	0.4769	0.3318	0.5487
~Support	0.8644	0.7963	**0.9095**	**0.7425**	0.8922	0.7868	0.8578	0.8072
Convenience	0.3609	0.5429	0.3147	0.5191	0.3646	0.4250	0.2758	0.5367
~Convenience	**0.9157**	**0.7400**	**0.9425**	**0.7382**	**0.9822**	**0.7999**	**0.9431**	**0.8176**
Fun	0.5245	0.5335	0.5071	0.5493	0.5523	0.4701	0.4674	0.5713
~Fun	0.7855	0.8547	0.8298	0.8645	0.8111	0.8906	0.7758	0.9135
Epistemic	0.4375	0.5215	0.4091	0.5433	0.4963	0.4838	0.3367	0.5524
~Epistemic	0.8395	0.7896	0.8606	0.7617	0.8169	0.7708	0.8777	0.8295
Social	0.3759	0.5560	0.3217	0.5829	0.4059	0.4572	0.3658	0.5940
~Social	0.8890	0.7251	**0.9148**	**0.6872**	0.8837	0.7378	0.8415	0.8002
Irritation	0.4993	0.8282	0.5049	0.8722	0.4728	0.7727	0.4705	0.8347
~Irritation	0.7641	0.5881	0.7599	0.5827	0.8312	0.5639	0.7445	0.6745

ping-related patterns and low convenience (~convenience) for all shopping patterns, including inner-city service usage. Additionally, low support (~low support) and low social benefits (~social) surpassed the threshold for situation-specific shopping. The consistency threshold value of the conditions surpassing the coverage threshold of 0.9 did not exceed 0.84. However, coverage values should be as close to 1 as possible for conditions to be considered necessary (e.g., Schneider and Wagemann 2012). As this was not the case, conditions exhibiting a consistency value above 0.9 were merely non-perfect necessary conditions (which is further elaborated on in the Web Appendix p. 12). Therefore, we decided against treating these conditions as necessary conditions during the next step of the fsQCA: Analysis of sufficiency. However, we will still refer to the results regarding the necessary conditions during the discussion of the results.

3.3.3 Identification of Sufficient Conditions

The next step in the analysis was the construction and minimization of a truth table to identify configurations of sufficient conditions leading to the same outcome. The starting point of the analysis was a truth table that contained all logically possible combinations of the tested conditions and their respective outcomes (e.g., Schneider and Wagemann 2012; Fiss 2011). To construct and analyze the eight truth tables (two for each shopping pattern), fsQCA 3.0 software (Ragin and Davey 2016) was used. To decide whether a combination of conditions in a given truth table row would be considered sufficient for the outcome, we initially set the minimum acceptable consistency threshold to 0.8 (e.g., Fiss 2011; Ragin 2008). After further adjustments, the final consistency cut-off values were higher than 0.8 (see Figs. 5 and 6 for final consistency cut-off values). The minimum number of cases for a given truth table row included in the analysis was 1 (see Web Appendix p. 12 for a more detailed description on the construction and analysis process).

The results of the truth table algorithm using the fsQCA 3.0 software for both high value-in-use and its negation (low value-in-use = ~value) are displayed in Figs. 5 and 6. The results highlighted the different combinations of conditions (i.e., paths) leading to the same outcome for each shopping pattern. They were based on intermediate and parsimonious solutions, and they displayed both core and peripheral conditions. Core conditions (big circles) are conditions that appeared in both the parsimonious and intermediate solutions, while peripheral conditions (small circles) only appeared in the intermediate solution, as they were eliminated during the minimization process to derive the parsimonious solution (Fiss 2011). Thus, core conditions represented stronger empirical evidence for the analyzed outcome than peripheral conditions (Fiss 2011). Therefore, we only focused on those paths containing core conditions. Each alphanumerical path represented a combination of identical core conditions as well as varying peripheral conditions. Black circles indicate the presence of given conditions (high), while white circles indicate their respective negation and, thus, their absence (low).

Different key parameters of fit (e.g., Ragin 2000, 2006, 2008; Fiss 2011; Schneider and Wagemann 2012) allowed us to assess our results (see Figs. 5 and 6)—coverage and consistency regarding the overall solution and coverage (both raw and

Shopping Pattern	# Combinatio	Monetary	Support	Convenience	Fun	Epistemic	Social	Irritation	Raw Coverage	Unique Coverage	Consistency
Experience Shopping	1a		•	⬤	⬤	⬤			**0.5360**	0.0051	0.9297
	1b			⬤	⬤	⬤		○	**0.5116**	0.0028	0.9280
	2a	○	⬤		⬤			◯	**0.5082**	0.0048	0.9090
	2b		⬤		⬤		•	◯	0.4751	0.0043	0.9254
	3		⬤	○	•	◯		◯	0.3502	0.0014	0.9167
	4	○			⬤	⬤		◯	0.4911	0.0198	0.8921
	5a	○		⬤	•			◯	0.4412	0.0008	0.9342
	5b		•	⬤		•	○	◯	0.3816	0.0019	0.9294
	5c	○	○	⬤		○	○	◯	0.2844	0.0055	0.9410
	6a		⬤		•	⬤	⬤		0.4758	0.0044	0.9329
	6b		⬤	•		⬤	⬤	•	0.2767	0.0038	0.9404
	7a	○	○			⬤	⬤	◯	0.2974	0.0042	0.9252
	7b		○	•		⬤	⬤	◯	0.2837	0.0014	0.9458
	8	◯			⬤		⬤	◯	0.4322	0.0240	0.9078
	9	⬤	⬤	◯	⬤		•		0.2943	0.0012	0.9392
	solution coverage: 0.802891 solution consistency: 0.862765 consistency cutoff: 0.895597										

Shopping Pattern	# Combinatio	Monetary	Support	Convenience	Fun	Epistemic	Social	Irritation	Raw Coverage	Unique Coverage	Consistency
Situation-Specific Shopping	1a		•	•	⬤	⬤		◯	**0.4687**	0.1099	0.9581
	1b	○		○	⬤	⬤	○	◯	**0.3523**	0.0220	0.9072
	2		⬤	○	⬤	○	○	◯	**0.3191**	0.0231	0.9447
	3		⬤	○	○	⬤	○	◯	0.2868	0.0066	0.9586
	4a	○	○		⬤		⬤	◯	0.3065	0.0331	0.9192
	4b			•	⬤	○	⬤	◯	0.2753	0.0050	0.9471
	5a	•		⬤	⬤	•	◯		0.2738	0.0116	0.9718
	5b			⬤	⬤	•	◯	•	0.2176	0.0017	0.9314
	6a	•	⬤	•		⬤	⬤	•	0.1714	0.0093	0.9802
	6b	○	⬤	○	•	⬤	⬤	•	0.1779	0.0050	0.9668
	7	○		•	•	○		○	0.3262	0.0088	0.9333
	solution coverage: 0.712349 solution consistency: 0.917004 consistency cutoff: 0.919614										

Notes: ⬤ = core condition (high); ◯ = core condition (low); • = peripheral condition (high); ○ = peripheral condition (low); blank space = does not matter if condition is high or low

Shopping Pattern	# Combinations	Monetary	Support	Convenience	Fun	Epistemic	Social	Irritation	Raw Coverage	Unique Coverage	Consistency
Bargain Hunting	1a		⬤	⬤	⬤	•		○	**0.5044**	0.0000	0.9800
	1b		⬤	⬤	⬤	•	•		**0.4596**	0.0028	0.9795
	1c	•	⬤	⬤	⬤		•		**0.4557**	0.0665	0.9794
	2a			⬤	•	•	•	○	**0.4881**	0.0221	0.9807
	2b	•		⬤	•	•		○	0.4522	0.0075	0.9769
	2c	•		⬤	•	•	•		0.4155	0.0014	0.9774
	2d	•	○	⬤	•		○	○	0.2896	0.0157	0.9679
	3	○	⬤		⬤	•		○	0.3871	0.0249	0.9603
	4a	•	•	○	⬤	⬤		⬤	0.2818	0.0114	0.9485
	4b	○	○	○	⬤	⬤	○	⬤	0.2284	0.0167	0.9596
	5	•	•	•	○	⬤	○	⬤	0.2295	0.0085	0.9598
	solution coverage: 0.759872 solution consistency: 0.970909 consistency cutoff: 0.951989										

Shopping Pattern	# Combinations	Monetary	Support	Convenience	Fun	Epistemic	Social	Irritation	Raw Coverage	Unique Coverage	Consistency
Inner-City Service Usage	1a		•	⬤	⬤	⬤	•		**0.4718**	0.0387	0.9276
	1b	•	•	⬤	⬤	⬤			**0.4026**	0.0076	0.9386
	2a	◯	○	○	⬤	⬤		◯	0.3368	0.0240	0.8955
	2b	◯		○	⬤	⬤	•	◯	0.3059	0.0053	0.9032
	3a	○		⬤	•		◯	◯	**0.3728**	0.0305	0.9408
	3b		•	⬤	•		◯	◯	0.3495	0.0076	0.9381
	4	⬤	◯	◯	⬤	○	•	◯	0.2225	0.0271	0.9196
	solution coverage: 0.712815 solution consistency: 0.911041 consistency cutoff: 0.90686										

Notes: ⬤ = core condition (high); ◯ = core condition (low); • = peripheral condition (high); ○ = peripheral condition (low); blank space = does not matter if condition is high or low

Fig. 5 Overview of the sufficient paths for the four shopping patterns and the high value-in-use outcome

unique), as well as consistency regarding the different solution paths that formed the overall solution for each shopping pattern and our two outcomes. The overall solution consistency values ranged from 0.84 to 0.97, and the coverage of the overall solutions ranged between 0.71 and 0.88. As both parameters could range between 0 and 1, with 1 indicating a perfect set relationship, our overall solutions all displayed relatively moderate to high values and, therefore, exhibited a good overall fit.

All the different paths exhibited high or very high consistency values ranging between 0.85 and 0.99 (see Figs. 5 and 6); in other words, all paths in any given solution for all shopping patterns were consistently sufficient combinations of their respective outcomes (high vs. low value-in-use). The coverage of each path in a so-

Shopping Pattern	# Combinations	Monetary	Support	Convenience	Fun	Epistemic	Social	Irritation	Raw Coverage	Unique Coverage	Consistency
Experience Shopping	1	∘	◯	◯		◯	◯		**0.7101**	0.0389	0.8939
	2a	∘		◯	◯	•	◯		0.3123	0.0202	0.9083
	2b			◯	◯	∘	◯	•	0.3959	0.0073	0.9514
	3	∘	∘	◯	◯	◯			**0.6686**	0.0084	0.9253
	4	∘		◯			◯	⬤	**0.4261**	0.0059	0.9298
	5		∘	◯		⬤	◯	⬤	0.2544	0.0052	0.9368
	6	∘	◯	∘	•			⬤	0.2711	0.0018	0.9451
	7	•	•	•	◯	•	◯	⬤	0.1932	0.0016	0.9531
	8a	◯		∘		◯		⬤	0.4163	0.0010	0.9424
	8b	◯			∘	◯	∘	⬤	0.3820	0.0010	0.9511
	8c	◯	•		•	◯	•	⬤	0.2066	0.0000	0.9385
	9	⬤	◯	◯	•	◯	•		0.2076	0.0112	0.9514
	10a		•	⬤	•	◯	•	⬤	0.2011	0.0000	0.9280
	10b	•	•	⬤	•	◯		⬤	0.1963	0.0018	0.9389
	10c	•	•	⬤		◯	•	⬤	0.1874	0.0002	0.9413

solution coverage: 0.842935
solution consistency: 0.866723
consistency cutoff: 0.908725

Shopping Pattern	# Combinations	Monetary	Support	Convenience	Fun	Epistemic	Social	Irritation	Raw Coverage	Unique Coverage	Consistency
Situation-Specific Shopping	1	∘	◯	∘	◯		∘	∘	0.5874	0.0372	0.9477
	2a	∘	◯		◯	◯	∘	∘	0.5484	0.0067	0.9543
	2b	∘	◯	∘	◯	◯			**0.7033**	0.0142	0.9007
	3		◯	◯	◯	◯	◯		**0.7052**	0.0161	0.9195
	4	∘	◯	◯		◯	◯		**0.7621**	0.0544	0.8560
	5	∘		∘	◯	◯	∘	∘	0.5509	0.0072	0.9499
	6a	∘	∘	◯	•		◯	⬤	0.2827	0.0034	0.9632
	6b	∘	•	◯	∘	•	◯	⬤	0.1819	0.0038	0.9674
	7	∘			•	◯	•	⬤	0.1810	0.0012	0.9718
	8		◯	∘	•	◯	•	⬤	0.1778	0.0006	0.9606
	9	∘	◯	∘	∘		⬤	⬤	0.1915	0.0064	0.9661
	10	◯	∘	⬤	•		⬤	⬤	0.1595	0.0006	0.9707

solution coverage: 0.87199
solution consistency: 0.841408
consistency cutoff: 0.895625

Notes: ⬤ = core condition (high); ◯ = core condition (low); • = peripheral condition (high); ∘ = peripheral condition (low); blank space = does not matter if condition is high or low

Shopping Pattern	# Combination	Monetary	Support	Convenience	Fun	Epistemic	Social	Irritation	Raw Coverage	Unique Coverage	Consistency
Bargain Hunting	1	∘	∘	◯	•	◯		∘	**0.3971**	0.0796	0.9781
	2a	∘	∘	◯	◯	◯	∘		**0.6392**	0.1139	0.9583
	2b	•	∘	◯	◯	◯	•	•	0.2318	0.0178	0.9449
	3a	∘	∘	◯	◯		∘	∘	**0.5593**	0.0321	0.9666
	3b	∘	•	◯	◯	•	•	∘	0.2499	0.0313	0.9230

solution coverage: 0.813441
solution consistency: 0.935584
consistency cutoff: 0.922967

Shopping Pattern	# Combination	Monetary	Support	Convenience	Fun	Epistemic	Social	Irritation	Raw Coverage	Unique Coverage	Consistency
Inner-City Service Usage	1	◯	∘	◯		◯	∘		**0.6795**	0.0597	0.9280
	2	◯	∘	◯	◯	◯			**0.6325**	0.0145	0.9565
	3a		∘	∘	◯	∘	•	∘	0.2110	0.0000	0.9645
	3b	∘	•	∘	◯		∘	∘	0.2023	0.0221	0.9470
	3c	•	∘	∘	◯	∘	∘	∘	0.1512	0.0031	0.9802
	3d	•	•	•	◯		•	∘	0.1459	0.0029	0.9479
	4a		∘	◯	•	•		⬤	0.1967	0.0131	0.9596
	4b	•	•	◯		•	∘	⬤	0.1540	0.0045	0.9416
	4c	•	•	◯	∘		∘	⬤	0.1596	0.0102	0.9728
	5		∘	◯	∘	◯	∘	⬤	**0.3362**	0.0064	0.9917
	6	∘	∘		∘	◯	•	⬤	0.1651	0.0000	0.9893
	7a	◯		∘	∘	•	◯	⬤	0.1884	0.0129	0.9617
	7b	◯	•		•	∘	◯	⬤	0.1645	0.0010	0.9795
	8a	∘	∘	⬤		◯	⬤	•	0.1457	0.0031	0.9879
	8b			⬤	•	◯	⬤	∘	0.1903	0.0078	0.8799
	9	∘			•	∘	•	∘	0.2345	0.0074	0.9007

solution coverage: 0.886584
solution consistency: 0.889073
consistency cutoff: 0.924242

Notes: ⬤ = core condition (high); ◯ = core condition (low); • = peripheral condition (high); ∘ = peripheral condition (low), blank space = does not matter if condition is high or low

Fig. 6 Overview of sufficient paths for the four shopping patterns and the "low value-in-use" outcome

lution was an indicator of its relevance for the analyzed outcome; therefore, higher coverage values indicated a path with a higher relative empirical relevance, even though all paths were part of the overall solution (Ragin 2006). Therefore, the raw coverage of a path was an indicator of how much of the outcome that specific path covered, whereas unique coverage indicated how much of an outcome was explained by that path that was not already explained by another path in the overall solution

(Ragin 2006). A more detailed presentation of the results across all shopping patterns can be found in the Web Appendix (p. 13–14).

Results for High Value-in-Use Across all shopping patterns, some overlapping paths and similarities emerged to have a high value-in-use, especially paths with high raw coverage values. This was especially evident if peripheral (supporting) conditions were taken into consideration. Experience shopping and inner-city service usage shared the same core conditions (high convenience, fun, and epistemic benefits) in Paths 1a and 1b, respectively, which were the paths with the highest empirical relevance for both shopping patterns. Additionally, Path 1a for experience shopping, situation-specific shopping, and bargain hunting displayed similarities in the combinations when peripheral conditions were considered. Similarly, Paths 2a and 2b of experience shopping and Path 2 of situation-specific shopping contained the same core conditions of high support and fun benefits. In addition, Paths 2a–d of bargain hunting and Paths 3a and 3b of inner-city service usage displayed several overlapping conditions (e.g., high convenience), even though they differed in their core conditions. While bargain hunting offered convenience benefits only as a core condition, the paths of inner-city service usage also contained low social benefits and low irritation. Overall, high evaluations of fun and convenience benefits were evident in almost all paths with high raw coverage values. This underlined their empirical relevance for reaching a high value-in-use. In addition, these findings supported the results from our PLS-SEM analysis. Furthermore, a high number of paths displayed a combination of both utilitarian and hedonic core and/or peripheral components, regardless of the shopping pattern, lending additional support to the PLS-SEM results. The results also pointed out some compensatory effects, such as Paths 2a and 2b for inner-city service usage regarding low monetary benefits. We could see that although low monetary benefits were perceived, the other benefit components compensated for this fact. This result supplements the PLS-SEM results regarding the non-significant monetary benefits in addition to the results regarding low value-in-use.

Results for Low Value-in-Use Across all shopping patterns, the results for low value-in-use as the outcome also showed several similarities, especially regarding paths exhibiting high raw coverage values. Path 1 of experience shopping (0.71) and Path 4 of situation-specific shopping (0.76) displayed the same combination of core (low support, convenience, epistemic, and social benefits) and even peripheral conditions (low monetary benefits), while Paths 2b and 3 also shared some similarities. Experience shopping and bargain hunting shared the same combination of core conditions in Paths 3 and 2a. In addition, bargain hunting shared a similar path (3a) with situation-specific shopping (1), supplemented by other similar, although not completely overlapping, combinations. Additionally, three shopping patterns shared a similar path if peripheral conditions were taken into consideration: Path 1 for experience shopping, Path 4 for situation-specific shopping, and Path 1 for inner-city service usage, all of which exhibited high empirical relevance. Overall, the results suggest that if low convenience benefits and/or low evaluations of hedonic components are evident in a combination, low value-in-use evaluations occur. This is especially the case in paths with high raw coverage values, which further underlines the importance of this benefit component in conjunction with the results of the necessary condition analysis. Therefore, these findings support and supplement our earlier findings regarding high value-in-use evaluations and PLS-SEM results. Additionally, the findings reinforce our previous notion on the importance of both utilitarian and hedonic components regarding value-in-use evaluations.

3.4 Sales Promotion as a Driver of Mobile Location-Based Services' Value-in-Use

To determine whether the type and number of relevant sales promotions sent to the users during an inner-city trip represents a possibility for the retailer to influence the customer's assessment of the value-in-use, we expanded the value-in-use model. As argued in Sect. 2.4, a distinction must be made between monetary and non-monetary sales promotions. For this purpose, the offers published during the survey period were categorized according to the grouping by Gedenk et al. (2010). As mentioned above, we assume that the number of available relevant monetary and non-monetary offers determines the content quality of a mobile LBS. For this reason, the relevance of an offer first needs to be operationalized. In this regard, the assumption was made that an offer was generally relevant for the customer if he or she actively clicked and opened it during a trip. The fact that the available offers were already filtered by customers' interests also supports this approximation. Therefore, we included the construct number of monetary offers and the number of non-monetary offers seen in the model as drivers of the value-in-use components. Also, we integrated the direct paths of the two constructs on the overall value-in-use. This resulted in an extended value-in-use model in which the value-in-use components served as multiple mediators between the two constructs' number of monetary and non-monetary offers seen and the value-in-use.

For the analysis, we again used SmartPLS 3.0 (Ringle et al. 2015) with a path-weighting scheme (Henseler 2010), a bootstrap procedure with 10,000 replications, and a blindfolding procedure with an omission distance of 7 (Hair et al. 2011). We checked the measurement model with a focus on the discriminant validity since the value-in-use measurement model was still the only multi-item construct. Tables A-12 and A-13 (Web Appendix, p. 15–16) summarize the results of the measurement model and the HTMT criterion. The assessment of the structural model is summed up in Table 5. The R^2 of the value-in-use model was 0.650, which is why the expanded value-in-use model still had moderate explanatory power ($0.5 \leq R^2 < 0.75$) (Henseler et al. 2009; Hair et al. 2019, 2011). The R^2 of the value-in-use components was within the range of 0.001 to 0.080 and was therefore very small (see Table A-14, Web Appendix, p. 17). However, since only two predictors were considered in the model, these low values were not surprising; they show that managing the number of relevant offers can only have a limited impact on the improvement of value-in-use. As Table 5 shows, the effect sizes are low. Only the number of seen monetary offers has a small effect size ($f^2 > 0.02$) on monetary benefits, social benefits, and support benefits. To indicate predictive accuracy, again, the Stone Geisser Q^2 value should be higher than 0 (Sarstedt et al. 2014; Hair et al. 2019, 2011), which applies

Table 5 Mediated value-in-use model: Results of the structural model

		Inner VIF Values	Coefficient	*p*-Value	f^2
DV: Value-in-Use					
–	*Number of Seen Monetary Offers*	1.286	0.150	0.000	0.000 (non)
–	*Number of Seen Non-monetary Offers*	1.193	0.029	0.408	0.003 (non)
–	*Monetary Benefits*	1.994	0.011	0.749	0.000 (non)
–	*Support Benefits*	2.909	0.120***	0.004	0.014 (non)
–	*Convenience Benefits*	3.116	0.210***	0.000	0.040 (small)
–	*Fun Benefits*	2.184	0.335***	0.000	0.147 (small)
–	*Social Benefits*	1.594	0.092***	0.002	0.015 (non)
–	*Epistemic Benefits*	2.039	0.183***	0.000	0.047 (small)
–	*Irritation*	1.118	–0.077***	0.003	0.015 (non)
DV: Monetary Benefits					
–	*Number of Seen Monetary Offers*	1.170	0.265***	0.000	0.064 (small)
–	*Number of Seen Non-monetary Offers*	1.170	–0.033	0.376	0.001 (non)
DV: Support Benefits					
–	*Number of Seen Monetary Offers*	1.170	0.248***	0.000	0.057 (small)
–	*Number of Seen Non-monetary Offers*	1.170	0.070**	0.041	0.005 (non)
DV: Convenience Benefits					
–	*Number of Seen Monetary Offers*	1.170	0.142***	0.000	0.018 (non)
–	*Number of Seen Non-monetary Offers*	1.170	0.058	0.106	0.003 (non)
DV: Fun Benefits					
–	*Number of Seen Monetary Offers*	1.170	0.120***	0.001	0.013 (non)
–	*Number of Seen Non-monetary Offers*	1.170	0.076**	0.031	0.005 (non)
DV: Social Benefits					
–	*Number of Seen Monetary Offers*	1.170	0.163***	0.000	0.023 (small)
–	*Number of Seen Non-monetary Offers*	1.170	0.027	0.462	0.001 (non)
DV: Epistemic Benefits					
–	*Number of Seen Monetary Offers*	1.170	0.124***	0.002	0.014 (non)
–	*Number of Seen Non-monetary Offers*	1.170	0.095***	0.006	0.008 (non)
DV: Irritation					
–	*Number of Seen Monetary Offers*	1.170	–0.031	0.425	0.001 (non)
–	*Number of Seen Non-monetary Offers*	1.170	0.005	0.897	0.000 (non)

Table 6 Mediated value-in-use model: Indirect effects

	Coefficient	*p*-Value
Total indirect Effects		
Number of Seen Monetary Offers → Value-in-Use	0.143***	0.000
Number of Seen Non-monetary Offers → Value-in-Use	0.065**	0.020
Specific Indirect Effects of Number of Seen Monetary Offers		
Number of Seen Monetary Offers → Monetary Benefits → Value-in-Use	0.003	0.753
Number of Seen Monetary Offers → Support Benefits → Value-in-Use	0.030***	0.009
Number of Seen Monetary Offers → Convenience Benefits → Value-in-Use	0.030***	0.006
Number of Seen Monetary Offers → Fun Benefits → Value-in-Use	0.040***	0.003
Number of Seen Monetary Offers → Social Benefits → Value-in-Use	0.015**	0.013
Number of Seen Monetary Offers → Epistemic Benefits → Value-in-Use	0.023***	0.009
Number of Seen Monetary Offers → Irritation → Value-in-Use	0.002	0.466
Specific Indirect Effects of Number of Seen Non-Monetary Offers		
Number of Seen Non-monetary Offers → Monetary Benefits → Value-in-Use	0.000	0.834
Number of Seen Non-monetary Offers → Support Benefits → Value-in-Use	0.008	0.103
Number of Seen Non-monetary Offers → Convenience Benefits → Value-in-Use	0.012	0.137
Number of Seen Non-monetary Offers → Fun Benefits → Value-in-Use	0.025**	0.038
Number of Seen Non-monetary Offers → Social Benefits → Value-in-Use	0.002	0.498
Number of Seen Non-monetary Offers → Epistemic Benefits → Value-in-Use	0.017**	0.017
Number of Seen Non-monetary Offers → Irritation → Value-in-Use	0.000	0.901

for all connections with the value-in-use components, except irritation (see Table A-14, Web Appendix, p. 17). Especially since only two value drivers were integrated into the model, the absence of endogeneity needed to be checked due to a variety of omitted variables that could have existed. Therefore, we applied again Park and Gupta's (2012) Gaussian copula approach in R-Studio[8]. We found that neither of the Gaussian copulas were significant ($p > 0.10$), as depicted in Table A-15 (Web Appendix, p. 18–20), which suggests that endogeneity was not present in the model and the results could be interpreted.

[8] Our analysis draws on the R code presented in Hult et al. (2018), which can be downloaded at https://www.pls-sem.net/downloads/gaussian-copula-files/.

In the first step, we examined the direct effects, as presented in Table 5, more closely. None of the direct effects of the number of seen non-monetary or non-monetary offers on value-in-use were significant, which points to a complete mediation through the value-in-use components (e.g., Nitzl et al. 2016). Moreover, it could be determined that significant influences existed on the six positive value-in-use components. Concerning the negative component of irritation, we found no significant direct effect. As assumed, monetary and non-monetary offers had different effects on the value-in-use components. While the number of seen monetary offers positively influenced all six positive value-in-use components, the number of seen non-monetary offers only influenced the hedonic value-in-use components of fun and epistemic benefits, and the utilitarian component of support benefits. Additionally, the influence of the number of non-monetary offers seen during a trip was consistently lower than that of monetary offers.

To determine the indirect effects of the number of seen monetary and non-monetary offers on the value-in-use, in the second step, we examined the total number of, as well as the specific, indirect effects (see Table 6) on the value-in-use. The total number of indirect effects of both the monetary and non-monetary offers seen was significant, whereby the effect of the number of monetary offers seen was significantly higher. Taking the results of the specific indirect effects from Table 6 into account, it can be stated that increasing the number of relevant monetary offers in mobile LBS leads to an improvement in value-in-use through an increase in fun benefits, support benefits, convenience benefits, epistemic benefits, and social benefits. The increase of relevant non-monetary offers available in the mobile LBS increases the value-in-use by increasing the fun benefits and the epistemic benefits. It should be noted that despite the significant direct positive influence of the number of non-monetary offers on the support benefits, no significant, specific, indirect effect on value-in-use via this component could be identified.

4 Discussion and Implications

Our results contribute to the research on digital services and the value-in-use construct in multiple ways, particularly in its evaluation of the usage of mobile LBS in inner cities. This study examined the influence of both user experience and shopping patterns as possible context factors on mobile LBS' value-in-use. In this vein, this study extends our knowledge of the goal dependence of customers' assessment of mobile LBS usage and of the temporally dynamic nature of this assessment. The results of our analyses confirm monetary, support, convenience, fun, social, and epistemic benefits, as well as irritation, as relevant value-in-use components, whereby fun, convenience, and epistemic benefits generally have the greatest relevance for the customer's value-in-use assessment. Furthermore, the fsQCA results show that different combinations of these components lead to high or low value-in-use. In contrast, combinations that avoid low value-in-use do not necessarily lead to high value-in-use. The fsQCA results thus underline the partly asymmetrical character of the relationships of high and low value-in-use values and the relevance of subgroups of value-in-use components for value assessment. Moreover, while support, convenience, social, and epistemic benefits had the same influence on value-in-use over the entire observed usage history, our results showed that the effect of monetary and fun benefits, as well as irritation, have a temporally dynamic influence, depending on the customer's user experience. Thus, as suggested by Helkkula et al. (2012a, b), value-in-use also depends on experiences from previous service events, and a dynamic understanding of value provides additional insights into such experiences.

More precisely, our results show that monetary benefits are not initially relevant to value assessment in the early phase of use, and only have a significant influence on value-in-use after the first three usage situations. However, this influence then continuously increases. Thus, our findings are generally in line with existing research. For example, the positive effects of financial incentives on intention to use LBA, as well as on the advertising value and positive influence of perceived monetary benefits on attitudes toward mobile coupon use, have already been demonstrated (e.g., Martins et al. 2019; Souiden et al. 2019; Achadinha et al. 2014; Kim and Han 2014; Richard and Meuli 2013; Dickinger and Kleijnen 2008). However, our study broadened the existing knowledge by showing that this relationship also occurs in the context of value-in-use. Moreover, the results on the temporally dynamic nature of the impact of monetary benefits and the finding that these monetary benefits are not relevant to value assessment from the beginning further contribute to the existing research. One possible explanation for this is provided by the channel expansion theory of Carlson and Zmud (1994); according to this theory, the perception of the potential benefits of a channel increases with increasing user experience, caused by improved competence of the customer. Against this backdrop, it can be assumed that customers initially pay attention to discovering the various functionalities of mobile LBS in order to familiarize themselves with how they work, and the financial benefits are weighed later. Another explanation for this phenomenon could be that the customers initially grant the mobile LBS advance trust about the financial incentives, which, however, decrease with increasing use; thus, from a particular point in time, the weighing of all further consequences of use against the generated monetary benefits begins.

A temporally dynamic effect on value-in-use has also been found for fun benefits, which are present from the first use and increase over time. A study conducted by McLean et al. (2020) investigated the influence of enjoyment, which is related to fun benefits, on an individual's attitudes toward an app within the initial adoption and usage phases. The authors showed that enjoyment is relevant in both phases. As with our results, the influence of enjoyment increased in McLean et al.'s (2020) study during continued use. However, our study extends the findings of McLean et al. (2020) by considering more than two service events and pointing out the connection to customers' value-in-use assessment. Since fun benefits also represented the most relevant construct for value-in-use assessment in our results, the conclusion is evident that hedonic aspects are taken into account in the customer-side use of mobile LBS. Thus, fun should not be neglected, even in functional mobile applications.

Furthermore, our results show that the influence of irritation on value-in-use also is temporally dynamic and only relevant in the early use phase. Also, the influence of irritation decreases with increasing user experience and is no longer significant after the fifth trip. The finding that irritation has a negative effect on mobile LBS' value-in-use is principally consistent with earlier findings, which found a negative influence of irritation on attitudes toward an advertising message (e.g., Ozcelik and Varnali 2019), on the perceived value of LBA (e.g., Lin and Bautista 2020; Xu et al. 2009b), on advertising value (e.g., Martins et al. 2019), on the attitudes toward LBS (Lin et al. 2013) and on the intention to use LBA (e.g., Richard and Meuli 2013). However, we illustrate here that this connection also exists in the context of value-in-use. Moreover, our finding that the relevance of the perceived irritation decreases with increasing user experience and that irritation is only significant in early use situations widened this existing knowledge. An explanation for this can be provided by channel expansion theory. According to this theory, it can be assumed that certain learning effects take place within the user, and the likelihood of irritation from mobile LBS usage occurring is reduced due to the user's increased competence and decreased feeling of being overwhelmed.

To address the context-dependency of value-in-use, seven shopping patterns were identified that can occur during an inner-city visit, depending on the respective objective. Based on the shopping motivation and the motives identified in this research area, the shopping patterns derived here represent combinations of similar motives that all follow the same goal. All seven shopping patterns were observed in our study, with experience shopping, inner-city service usage, and situation-specific shopping being the most common, followed by bargain hunting, social shopping, habitual shopping, and convenience shopping. Also, in view of the sample sizes, the four shopping patterns of experience shopping, situation-specific shopping, bargain hunting, and inner-city service usage were examined in depth using fsQCA.

The findings from our fsQCA showed that even though the results for each of the four shopping patterns and both outcomes displayed different sufficient paths, some combinations of core conditions between the shopping patterns overlapped. Therefore, the results point out several similarities between shopping patterns, especially regarding paths with high empirical relevance for their respective outcomes. Consequently, the findings indicated that customers' shopping patterns influence the evaluation of the usage of a mobile LBS app somewhat in inner cities as a context factor; however, according to our data, its impact is not as differentiated as expected. Thus, a certain degree of generalization of the value-in-use conceptualization of shopping patterns can be shown, which is a relevant result for research and management, even if it contradicts the underlying assumption of the study. However, the fsQCA also disclosed shopping pattern-specific findings, which leads to the conclusion that all seven value-in-use components are relevant for all shopping patterns, despite the fact that they have different effects on generating high and avoiding low value-in-use. A possible explanation for this result could be that the multifunctionality of mobile LBS has features for a wide range of usage situations and objectives, which is why mobile LBS usage creates a basic benefit independent of specific goals.

Management of the offers published in the mobile LBS can be used as an instrument by inner-city retailers looking to influence value-in-use. For this reason, the possibility of influencing value-in-use was also examined in this study. As existing research on sales promotions suggests, a distinction was made between monetary and non-monetary offers (e.g., Büttner et al. 2014; Yi and Yoo 2011; Gedenk et al. 2010;

Chandon et al. 2000). The relevance of these offers was also taken into account by considering the number of monetary and non-monetary offers actively seen by the customer as value drivers. It was assumed that the number of seen offers was a good indicator of their relevance. The results show the impact of the type and number of relevant transmitted offers. The results also indicate that the number of existing relevant monetary and non-monetary offers can only be used to influence positive value-in-use components and do not influence the negative component of irritation. Furthermore, the results show that the influence of the number of relevant monetary and non-monetary offers on the value-in-use is fully mediated by the components of the value-in-use; however, they have no direct effect on the value-in-use. Consistent with existing research (e.g., Buil et al. 2013; Reid et al. 2015; Büttner et al. 2014; Yi and Yoo 2011; Chandon et al. 2000), this study showed that monetary and non-monetary offers have different effects. Both offer types have a positive, total, indirect influence on value-in-use. Therefore, the influence of the number of seen monetary offers is markedly stronger than that of non-monetary offers, which is in line with the findings of sales promotion research (e.g., Alvarez and Casielles 2005; Gilbert and Jackaria 2002; Chandon et al. 2000). However, the adverse long-term effects of monetary sales promotions, which do not exist in the case of non-monetary sales promotions (e.g., Buil et al. 2013; Yi and Yoo 2011; Mela et al. 1997), must be taken into account, which is why monetary offers should not generally be preferred over non-monetary ones. Also, in line with our research results, the transmission of relevant monetary offers affects both hedonic and utilitarian value-in-use components (e.g., Sinha and Verma 2020; Reid et al. 2015; Büttner et al. 2014; Chandon et al. 2000). In contrast, non-monetary offers only affect hedonic (fun, epistemic) value-in-use components (e.g., Sinha and Verma 2020; Reid et al. 2015; Büttner et al. 2014; Chandon et al. 2000). These findings can be used to manage value-in-use through the information and offers delivered by the mobile LBS. However, it is important to be aware that the number of relevant offers has only a limited possibility of influencing the value-in-use, as low coefficients of determination and effect sizes indicate.

Furthermore, in our study the users' data were collected immediately after actual use, not from scenario-based labor experiments. Field studies are preferable to laboratory experiments, especially in the context of mobile services if overall acceptability and influencing factors, such as system functions and the impact of usage contexts, are the object of investigation (Kjeldskov and Stage 2004; Van Elzakker et al. 2008; Christensen et al. 2011; Sun and May 2013). Thus, high external validity can be assumed in our results, as evaluation-relevant environmental factors were present. Moreover, the measurement of value-in-use over various service events can be considered a further contribution of our study. With the integration of user experience as a moderator, the boundaries of the analysis of single static service experiences can be overcome to reveal dynamic relationships between past and present value assessments. In line with Helkkula et al. (2012b), this allowed a deeper understanding of the temporally dynamic nature of value-in-use. Also, our study contributes to the value-in-use and mobile LBS research fields by using a mixed-methods approach that combined PLS-SEM, including moderation and mediation analyses and fsQCA, to analyze the data. PLS-SEM was used to explain the causal paths that compose value-in-use as well as the moderating effect of user experience, whereas fsQCA was used to gain a deeper understanding of the complex, asymmetric, and synergistic combinations of different value components that lead to high or low value-in-use in respective shopping patterns. Therefore, the combination of both methods provided a complementary and more comprehensive view of value-in-use of a mobile LBS for different goal-orientated shopping patterns and user experience.

Our research entails several managerial implications and implies challenges regarding the development and use of mobile LBS in inner cities. By increasing the monetary, support, convenience, fun, social, and epistemic benefits perceived by the customer and reducing irritation during use, the customer's perception of mobile LBS' value-in-use can be increased independently of the shopping pattern. Thus, shopping pattern-specific targeting is not necessarily required. Moreover, both hedonic and utilitarian benefits that can be perceived by the customer during LBS use should be considered simultaneously in the management of mobile LBS, even if the mobile LBS seems to contain more functional features. Thus, our results support hedonic components' high relevance—an important result in that retailers using retail technologies have, so far, seemed to focus on utilitarian components (Willems et al. 2017).

Findings from the information systems success research as well from the mobile application design research provide relevant hints to identify suitable possibilities for affecting both the utilitarian and hedonic mobile LBS' value-in-use components (e.g., Hsu and Tang 2020; DeLone and McLean 1992, 2003, 2016; Kumar et al. 2018; Magrath and McCormick 2013). In the scope of these research streams, amongst others, the app interface is discussed. The app interface should be attractively designed, mainly because the visual aesthetics have a significant influence on perceived ease of use, usefulness, and enjoyment of mobile app use (Kumar et al. 2018). According to Kumar et al. (2018), relevant dimensions of visual aesthetics in the mobile app context are coherence (provision of consistent and meaningful information through organized and orderly app-building), complexity (visually perceived richness triggered by app functions and design), and legibility (interactivity provided by the ease of labels/icons/links). In the following, insights from the design research are used to present individual management suggestions impacting the seven value-in-use components.

The app design needs to be coherent and legible (Kumar et al. 2018) to influence *convenience benefits* through mobile LBS design and functionalities. Thus, app planners should make sure that the app's menu navigation is easy to understand, intuitive, and consistent so that users do not perceive higher learning costs. Furthermore, elements for customizing the LBS content should be integrated so that users can adjust the functionality to their individual preferences. Our results regarding necessary conditions also point out that it is important to avoid low evaluations regarding convenience benefits to circumvent low value-in-use evaluation. Additionally, high convenience evaluations are part of different combinations that lead to high value-in-use assessments, further emphasizing the importance of such avoidance. Moreover, perceptions of convenience benefits can be positively influenced by increasing the number of existing relevant monetary offers in mobile LBS.

The creation of *support benefits* by assisting the customer in fulfilling his tasks is also important for the customer's value assessment. It can be improved by increasing the number of relevant monetary offers. Furthermore, a complex, coherent, and legible app design increases perceived usefulness (Kumar et al. 2018) and therefore creates support benefits. Retailers should carefully check the information quality (DeLone and McLean 1992, 2003, 2016) and share content that is accurate, complete, up-to-date, and relevant to the customer. Additionally, the information provided should offer added value to offline shopping, which is why, for example, more in-depth product information, images, and videos or use instructions should be provided. Customer ratings could be integrated to further support the customers in achieving their goals, encouraging interactivity. Overall, however, the legibility should always be taken into account so that the relevant content can be found and processed efficiently and comfortably to avoid information overload. Accordingly, various customization options should be integrated so that the mobile LBS' content and functions can be dynamically adapted to customer goals. Further, service quality must be ensured by offering the customer fast, efficient and goal-oriented assistance in the form of digital customer service (DeLone and McLean 2003, 2016), which can be integrated into the mobile LBS, for example, through various contact options, chats (in person or via chatbots) or FAQs.

As our findings regarding necessary conditions for low value-in-use evaluations point out, users' perceptions of low monetary benefits should be avoided. Therefore, ensuring a positive evaluation of *monetary benefits* is important for inner-city retailers and should also not be underestimated by inner-city service providers. It is important to note that ensuring a positive evaluation of monetary benefits during mobile LBS use merely seems to avoid low value-in-use evaluations. However, it does not automatically lead to high value-in-use evaluations, as it is not a (perfect) necessary condition for high value-in-use and not always part of sufficient paths that lead to high value-in-use. Monetary benefits are especially relevant for more experienced users, whereby the relevance increases with user experience. One way of influencing this is to increase the number of existing relevant monetary offers transmitted by a mobile LBS. The specific form of offer is to be determined individually by the respective retailer. Numerous types of sales promotions are possible, such as coupons, loyalty discounts, packages with extra content, or price reductions (Gedenk et al. 2010). Hsu and Tang (2020) show that prizes/sweepstakes, gift exchange certificates, and electronic coupons are primarily relevant in the mobile app context and positively influence the app stickiness, which "refers to the application of the concepts of loyalty or continuance behavior to websites or virtual communities" (Hsu and Tang 2020, p. 69–70). Magrath and McCormick (2013) also show that product promotions (vouchers, incentives, rewards, discounts, competitions, social media) are an essential app design element. Gamification campaigns with financial incentives are also suitable.

The generation of *fun benefits* is the most important way of influencing value-in-use and is of central importance across all shopping patterns. Their perception becomes more important for customers over time, which is why the consideration of stimuli that trigger positive emotions such as fun is especially important to encourage continued use due to high value-in-use. The perceived fun benefits can be increased by increasing the transmission of both relevant monetary and non-monetary offers. A complex, coherent, and legible app design is crucial for generating fun benefits (Kumar et al. 2018). Moreover, the transmitted content and its design play a central role. Retailers should not only try to inform customers but also offer them entertainment at the same time, for example, by making their own videos or by personal branding. Besides, gamification provides further ways to create fun benefits and can strengthen customer loyalty for both retailers and mobile LBS (Hwang and Choi 2020). For example, digital lotteries and bingo games can be organized or point collection campaigns initiated, enabling participants to receive discounts, product bonuses, or extra services.

Epistemic benefits should also be addressed to avoid low mobile LBS' value-in-use during an inner-city visit for all shopping patterns. This can be achieved by increasing the number of transmitted relevant monetary and non-monetary offers, and letting users discover new stores and service providers that they have never visited before (Betzing 2018). Additional information about a specific retailer and its assortment, which was not known via conventional channels so far, offers a further possibility to create epistemic benefits. Community platforms can also be installed, which increase interactivity between customers. Following the example of Instagram, they create opportunities to learn new things through other customers' experiences and be inspired by them.

The generation of *social benefits* could also be addressed, as it is possible to influence them by increasing the number of transmitted relevant monetary offers. Additionally, principles used in gamification may enhance evaluations of the app further by, for example, offering customers the possibility to compare themselves with other mobile LBS users in the inner city, thus providing social benefits. The creation of social benefits through mobile LBS use can, for instance, be supported by a social media campaign and well-directed influencer marketing. On the one hand, this draws attention to the mobile LBS, and, on the other hand, its use can be given a positive image, which can have a positive influence on the customer's self-image. Furthermore, social benefits within the mobile LBS use can be enhanced and strengthened with gamification as part of the community platform, like insights in the fitness app context indicate (e.g., Hassan et al. 2019). For example, a scoring model can be installed, which allows customers to compare themselves with each other, or digital scavenger hunts can be organized.

Customers' perceptions of *irritation*, especially during first use and in the early use phase, should also be avoided. For this purpose, the app design should be clear and simple. Moreover, the customer should be offered possibilities for customization of the app design and functionalities. Since the irritation is particularly relevant in terms of the first trips' assessment, the onboarding process could be designed so that the most important functions and settings are explained to the customer clearly and understandably right at the beginning of the app use. However, perceived irritation cannot be influenced by the number of relevant monetary and non-monetary offers transmitted. This does not mean that the perception of irritation is independent of the total number of offers available. As previous research shows, irritation created by information overload and irrelevant offers have negative effects (e.g., Swar et al. 2017; Im and Ha 2015; Achadinha et al. 2014; Dickinger and Kleijnen 2008). Therefore, the app provider should give users different customization options regarding the app's design and the information displayed (e.g., by using user-provided interests as filter variables), as well as in which way (e.g., push/pull) and how often a user receives notifications from the app (e.g., Souiden et al. 2019).

5 Limitations and Future Research

While our study contributes to the research on value-in-use, it also has limitations that offer avenues for future research. *First*, our study was based on a sample of business students, which limited its findings to this age group; therefore, it is not representative. Additionally, the students in our sample were first-time users who used the presented mobile LBS during a two-month period. Consequently, our results were limited to the experiences of the early usage phase, which is why no statements could be made about the customers' evaluation of long-term use whereby mobile LBS use is entirely integrated into the customers' use processes. In order to gain further insights into the temporally dynamic nature of value assessment, a longer-term measurement of value-in-use in further service events is necessary. Such research could, for example, investigate whether the increasing influence of fun benefits continues to rise over time or whether this influence will be stable from a particular point in time or even decrease. Therefore, future researchers should test our proposed conceptualization in a broader setting and record long-term data to discover possible changes in value-in-use evaluations over the long term. Nevertheless, the available data can be used for further analyses that take greater advantage of the longitudinal nature of our data set. For example, multi-level modeling could be used to include intra-subject as well as inter-subject differences, and thus consider the nested structure of the data at the two levels of customer and time (Hoffman 2015). Moreover, only evaluations for inner-city trips actively started by the customers were collected during this field study, which excluded other usage situations with the mobile LBS. Since the value-in-use perceived by the customer is also relevant in other usage scenarios, such as obtaining information at home using the information provided by the mobile LBS, it is necessary to conduct further research in this area as well.

Second, self-selection bias in this study was probable, as the students were invited to participate. Thus, our study was limited in that participants had a positive attitude toward the use of the LBS app, and the results of this study should only be interpreted for actual users. The value perceptions of people who refuse to use the app on principle may differ. Further research should, therefore, focus on the differences in value-in-use assessment between users and non-users. It would be interesting to investigate the extent to which value-in-use differs from the envisioned value-in-use. Such a study could also examine the extent to which privacy concerns act as a knock-out criterion for actual use. There is also the possibility that a particular social desirability bias exists in our study, as the participants knew that the mobile LBS was developed at their university. However, both positive and negative assessments and comments regarding usage of the app were given; thus, we presume that this bias was not too strong. Since our study was based on a prototype of a mobile LBS, application of the value-in-use conceptualization presented here in another research setting with an already established app would be desirable.

Third, we did not have any control over the content and design of the offers that our participants received; therefore, perceptions of monetary benefits may have been lower, as retailers might not have targeted student participants with their offers, even though existing research has shown that an offer's tailored content is an important driver of attitude toward and redemption intentions of LBA (e.g., Martins et al. 2019; Bauer and Strauss 2016; Lin et al. 2013). Also, we approximated the relevance of an offer by the customer actively clicking on that offer. It cannot be guaranteed that some offers were viewed for other reasons and were, therefore, not directly relevant to the customers. Furthermore, our results regarding the type and number of transmitted offers were limited to the relevant offers. However, as current research shows, the risk of information overload and the fear of spam is relevant to the LBA context (e.g., Swar et al. 2017; Im and Ha 2015; Achadinha et al. 2014; Dickinger and Kleijnen 2008). Thus, further research is needed that examines the impact of the type and number of irrelevant offers that are made. Other drivers related to these offers should also be investigated.

Fourth, we had to exclude 37.5% of the data sets as part of the data cleansing process because they were incorrect or incomplete (25.74%), the evaluations could not be assigned to a trip (6.94%), or the trips were shorter than ten minutes or longer than ten hours (4.85%). This high proportion of exclusions in the context of data cleansing was mainly due to the field study setting, despite leading to an improvement in the external validity of the results. Unfortunately, potential value-in-use assessments at various service events were lost through this data cleansing, which probably contributed to the results. They way in which positive and negative value assessments were distributed in these trips cannot be sufficiently clarified, which is why there is a principle risk that negative assessments were not fully included in the analysis due to technical problems with the mobile LBS. Should this have happened, the estimated path coefficients would have potentially been somewhat overestimated, which is why replication of the results of our study might be necessary. On the other hand, the inclusion of inaccurate data, which may not represent the actual value-in-use assessment during mobile LBS use on the trip in question, would also be a potential source of biased estimates, which justifies the exclusion from our point of view.

Fifth, even though all seven shopping patterns occurred in the trips, the sub-sample sizes of the patterns of social shopping, habitual shopping, and convenience shopping, as mention above, were too small to be included in the fsQCA analysis. Thus, shopping pattern-specific findings were limited to the other four shopping patterns, making further research necessary. Further studies could analyze goal-oriented shopping patterns as they relate to value-in-use in more detail and thus expand the findings presented in this study. In particular, the connection between specific sub-functions of the mobile LBS and the focal goals of the respective shopping patterns could be examined in a future study based on our findings. Notably, another research gap exists in this context concerning the influence of the interaction between shopping patterns and goal-congruent offers, which are provided through the mobile LBS during trips, on the value-in-use perceived by the customer.

Sixth, six positive and one negative value-in-use components were identified in our value-in-use conceptualization. However, other components of value-in-use exist, especially concerning the perceived drawbacks of use. A higher-order construct could provide further insights by deepening the understanding of the different facets of the more abstract value-in-use components presented here.

Seventh, to minimize privacy concerns and increase customers' willingness to participate, it was decided that as little personal data as possible would be collected from the participants. Furthermore, we have no reliable data on actual redemptions of offers displayed on our participants' devices and are therefore unable to link actual value-in-use evaluations of the app during specific shopping trips to users' behavior. Further research in this area could investigate the influence of a positive mobile LBS' value-in-use on retailer-relevant variables, such as visit frequency and sales volume.

Lastly, our study focused on users of a mobile LBS during inner-city visits as one actor in a service ecosystem comprised of several actors whose contributions are crucial to users' value-in-use assessment. Adjacent to app users and app providers, inner-city retailers, inner-city service providers, and even city marketing must co-operate to provide users with relevant and valuable app content (Bartelheimer et al. 2018). While an app provider must ensure the app's technical functionality as well as provide an IT environment for inner-city retailers and service providers, retailers and service providers need to contribute to the information (e.g., describing the app, discussing details about its offerings, offering coupons, etc.) and other content visible to the app's users (Bartelheimer et al. 2018). Therefore, the app provider supplies the resources that retailers and service providers can use to increase their own visibility for app users and achieve advantages over online retailers. This view is consistent with the service-ecosystem perspective, which goes beyond dyadic interactions to instead take a broader approach entailing multiple actors (Frow and Payne 2019; Bartelheimer et al. 2018; Betzing et al. 2018; Becker et al. 2019). Therefore, future research should focus on the service ecosystem as a whole and its impact on users' value-in-use evaluations (Frow and Payne 2019), as this would advance research on (digital) service ecosystems.

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