Why Do We Share Where We Are?

The Influence of Situational Factors on the Conditional Value of Check-In Services

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Abstract

Location-based services (LBS) are among the major advancements in mobile internet applications since they take into account the geographic location of an entity and the ubiquitous nature of mobile services, using spatial decision support to provide customer value that exceeds that of traditional channels. However, the growth trajectory and associated adoption and diffusion of LBS have slowed, as challenges related to consumer perceptions persist. This study focuses on check-in services (CIS), a kind of LBS, like Facebook Locations and Foursquare, which use shared user experiences linked to geographical information to recommend places and venues. User adoption of CIS is particularly challenging, as the potential of location tracking is often regarded as a “double-edged sword” that benefits decision-making but risks the loss of privacy. To gain insights into users’ voluntary CIS information disclosure, we combine the privacy calculus model (PCM) with the concept of conditional value and explore the effects of various situational stimuli in a true experiment and in data analyses that combine group comparisons with structural equation modelling (N = 296). The study confirms the relevance of conditional value to PCM and outlines direct and indirect effects of the situational factors of place relevance and frequency of location visit. The study makes several theoretical and practical contributions to the field of LBS adoption.

Keywords: Location-based services, check-in services, system adoption, conditional value

1. Introduction

Location-based services (LBS) are among the major advancements and most influential categories in mobile internet applications [1, 2] as they take the geographic location of an entity into account [3]. Estimates suggest that LBS will generate up to \$700 billion in value to consumer and business users [4] and that the global LBS market will grow from \$15.04 billion in 2016 to \$77.84 billion in 2021 [5]. While traditional technology-adoption research has examined LBS with regard to consumer perceptions [6-8], it has not addressed the specific attributes of applications and services, including situational factors [9, 10]. Aspects of functionality, such as perceived ease of use and perceived usefulness, are weak adoption predictors in the case of “native” users of digital applications [11]. Users’ adoption of interactive applications like LBS is predominantly determined by users’ perceptions of the services’ value [2]. The ability to measure the benefits that increase the value of location disclosure will contribute to the quality of LBS and the effectiveness of the respective business models [12]. Among the perceived risks of LBS, the risk to privacy has been one of the major challenges of LBS adoption since its introduction [13, 14]. Users often refuse to reveal their locations because they are concerned about the possibility of abuse of location-based information [14].

The relationship between the perceived benefits and risks and their influence on user acceptance have been explained with the privacy calculus model (PCM) [15, 16]. However, research has focused on an unspecific and static concept of perceived benefits that does not address the dynamic nature of location in a mobile setting [e.g., 16, 17]. This study focuses on one category of LBS, check-in services (CIS). These services provide particularly valuable LBS, as they automatically combine location, time, and identity information to support decision-making. Services like Foursquare collect and analyze location-based user data and recommendations from a community to suggest “places to eat, drink, shop, or visit in any city in the world.”¹ Such services require an active community to provide decision support, but the individuals who

¹ www.foursquare.com

provide the data may not directly benefit from the service, instead sharing their experiences with others to support them. Despite the popularity of these services, how users' perceptions of CIS' benefits, risk, and value is established remains unclear [18]. In particular, research has not yet addressed the situational contexts in which CIS are used. Since the value of LBS arises from specific situations, the situational context is highly relevant to that value, so we address this research gap with an experimental study and build on PCM [15, 16] to explore the situational influence factors that determine the conditional value of CIS and the related intention to disclose personal information. The related research questions are:

RQ1: How can the concept of conditional value be used with the PCM to explain CIS information disclosure?

RQ2: How do situational factors contribute to the generation of conditional value and CIS information disclosure?

We proceed as follows: First, we discuss LBS and CIS and the theoretical foundation of the study. Then, based on this discussion, we develop the research model. Next, we describe the methods applied in the paper and the related results, followed by a discussion of the theoretical and practical implications. We conclude with a summary of our contributions.

2. Related literature

This section defines the specifics of LBS and CIS and outlines the theoretical foundation of our study.

2.1 Location-Based Services and Check-In Services

We focus on users' geographic location information, which can be "any type of data that places an individual at a particular location at any given point in time, or at a series of locations over time" [19]. We define LBS as 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 [13, 20, 21].

This work follows the call for context-specific research in the area of LBS [16, 22] by focusing on CIS as an application area of LBS. CIS allow users to “make their personal and location data publicly available through the (...) apps that allow users to ‘check in’ by publicly registering their current location for social purposes” [23]. Prominent examples in this category are Foursquare² (or its derivative, Swarm³) and Facebook Places⁴. Users use such services for such purposes as documenting places and telling stories about a location [1]. The location check-ins can also act as a decision aid for other users who are considering visiting a venue, as friends’ visits are recorded and made available electronically. However, check-ins are not limited to venues and can be used at every location and at any point in time. Check-ins may be made during a visit to a club in another city, a sports stadium, or places visited daily, such as parking lots and grocery stores, so these check-ins allow a certain user to be “followed” without physically accompanying him or her [18].

Context elements	Example
	Location + Time + Identity	Foursquare, Facebook Places, Google Latitude
	Location + Time	In-car navigation, Telstra Whereis, Mobile Google Maps
	Location	Paper maps, Desktop Google Maps

Figure 1: Characteristics and value propositions of LBS [24]

Some LBS take only the user’s location into account [26], such as when Google Maps is used on a desktop to explore a foreign country (see Desktop Google Maps in Figure 1). However, Google maps can also take the time into account, as when it is used on a mobile device for GPS navigation, combining the current location with current traffic conditions. Therefore, we included mobile Google Maps in the location and time category in Figure 1. LBS can also use the user’s

² <https://foursquare.com/>

³ <https://de.swarmapp.com/>

⁴ <https://de-de.facebook.com/places/>

identity to “remember” where he or she has been before. Related applications like Foursquare provide a particularly high level of value for their users (see Figure 1). However, also non-CIS applications like some locational social media, geographic and mobile customer relationship management (CRM), and some governmental intelligence applications can be assigned to the category that combines location, time, and identity [e.g., 25]. CIS are an ideal example, as they belong to this most sophisticated class of LBS. In addition, CIS are particularly suitable for the underlying research questions, as CIS rely on voluntary (and, therefore, conscious) disclosure of location. Such conscious decision-making is well suited to investigate the influence factors of these decisions, and using it follows the call for further examination of voluntary cases of information disclosure [22].

2.2 The Theoretical Lens of the Privacy Calculus Model

Acceptance research in the domain of LBS has used several theoretical lenses. While many studies are based on the Technology Acceptance Model and related concepts like Venkatesh et al.’s [26] Unified Theory of Acceptance and Use of Technology [e.g., 27, 28], their applicability to the present research is questionable, as these models were developed in the context of the acceptance of mandatory technologies in an organizational context and do not take into account the intrinsic motivations for the everyday-life use of a technology [29, 30]. These models also focus on a technology’s capabilities, so contextual factors and their influence on the perceived risks and benefits are neglected [29, 31].

Therefore, we build on the PCM as a theoretical foundation to explain the use of CIS [15, 32]. At the individual level, privacy refers to an individual’s ability to control how his or her personal information is used [33]. PCM is based on exchange theory, as it proposes that the individual decision is whether to disclose information, such that privacy is lost in exchange for the benefits of the service [34]. This benefit-risk exchange results in a privacy calculus that takes into account the perceived costs in the form of privacy risk and the benefits of the respective service [15, 32].

In case that the benefits exceed the cost then this results in an intention to participate in the exchange by disclosing personal information. To that end, the intention to disclose is highly relevant for the acceptance of a service [16, 35]. PCM was chosen as the theoretical foundation, as privacy is regarded as the major inhibiting factor in adopting LBS [14], but more research on the relevance of privacy risk to the decision to share real-time location data is required [23, 36]. PCM is also particularly suitable, as services like CIS are usually free to use, but the user “pays” by providing personal data. PCM takes this trade-off into account and has been described as “the most useful framework for analyzing contemporary consumer privacy concerns” [15].

PCM also allows service-related benefits to be examined simultaneously [33] and has been successfully applied in various contexts [e.g., 34, 37]. It is also highly flexible, as there is no established set of factors for benefits and costs [38]. For example, the benefits applied in the case of e-commerce range from personalization [39] to personal interest in internet content [34] to enjoyment [40]. In this context, the flexibility of the approach allows us to tailor the benefits and privacy risks to the special characteristics of CIS to enhance the results’ relevance to our area of interest.

2.3 Integration of Conditional Value and Situational Factors

We use the concept of conditional value to determine the benefits of CIS. Pihlström and Brush [41] called for mobile service research to integrate the dimensions of time and location into the service-creation process. The related construct of conditional value is defined as the value experienced only in certain contexts or situations based on a particular time or the user’s location, social environment, technological environment, or mental state [41]. The service is available independent of these conditional factors—ideally everywhere and at all times—but conditional value emerges only when the service is used based on the situation [41]. Time and place are the strongest predictors of conditional value [42], as “context is everything” for the interaction between the service and the user [43]. Conditional value is particularly suitable for a study of

LBS, as it captures the value that arises when the service is encountered in a location-specific context [35, 44]. CIS takes this idea even further, as they use, along with time and identity information, even more contextual aspects of a situation (see 2.1.1). Conditional value has been suggested as a driver of acceptance [45], but since “each context provides conditions under which different resources will and will not be valuable” [46], research on the factors that influence conditional value is still rare [47].

In this study on CIS, we replace the perceived benefits in the PCM with the more specific concept of conditional value and argue that the privacy calculus weighs conditional value against perceived privacy risk. In line with Xu et al. [16], we expect that the outcome of the privacy calculus results in perceived disclosure value, in this study defined as the perceived utility after considering privacy risk and conditional value (Table 1). In the next section, we build our research model around this privacy calculus in order to identify factors that influence the perceived conditional value in the context of CIS.

3. Hypotheses Development

The research model contains the constructs of the PCM and the related information disclosure intention as well as the drivers of conditional value whose relationships are explained in the following sections.

3.1 The Privacy Calculus of CIS

Conditional value, the core concept in our research model, represents the pivotal benefit associated with the use of check-in services [44]. Studies have demonstrated empirically that commitment and behavioral intentions are heavily influenced by conditional value [45]. We argue that conditional value specifies the more general construct of “benefits” included in the PCM [15]. Conditional value is more suitable than unspecific benefits as it is a dynamic concept that uses aspects of the situation to measure a momentary value that changes over time [41], so conditional value represents the beneficial element of the benefit–cost analysis that is performed

in PCM to determine CIS' disclosure value (Table 1). Based on this line of argumentation, we hypothesize that:

H1: A CIS' perceived conditional value is positively related to the perceived disclosure value of the CIS' information.

The perception of the information disclosure's value influences the user's decision to disclose personal information by using CIS. The decision to purchase traditional goods is driven by the perception of the goods' value, so a greater perception of value increases the willingness to buy [48]. For services, the greater the perceived value the greater the behavioral intention to use the service [49]. Xu et al. [16] showed that, in the context of LBS, the disclosure value that results from the privacy calculus influences the intent to disclose. Thus, CIS' disclosure value influences CIS' disclosure intention. For instance, if the benefit to share a check-in location publicly exceeds the perceived risk that the data will be abused for advertisements then the individual will be more likely to accept CIS information disclosure. We propose:

H2: The perceived value of a CIS' information disclosure is positively related to the user's intention to disclose.

Perceived privacy risk is included in the PCM as a counterpart to the perceived benefits and is required in performing the cost-benefit analysis when estimating the disclosure value of information [15, 16]. Perceived privacy risk has been found to have a negative impact on the value of information disclosure in relation to LBS [16], but privacy concerns can also directly influence the perception of benefits [50]. Hence, we suggest that the perceived privacy risk influences the privacy calculus in the form of a CIS' disclosure value. Privacy risk also exerts a negative impact on conditional value with which we replace the more general benefits of information disclosure in previous studies. We propose:

H3: Perceived privacy risk is negatively related to a CIS' conditional value.

H4: Perceived privacy risk is negatively related to the disclosure value of CIS.

3.2 Drivers of Conditional Value

With the first extension we follow the call to integrate extroversion into research that relates to privacy and use intentions [22]. Even though our main interest is the influence of situational factors, we could control the influence of personality with this construct. Extroverted tend to be “outgoing and social” [51], so they are more prepared than others are to disclose information online, as they perceive this activity as an extension to their offline lives [52, 53]. In this vein, extroversion is found to be positively related to the depth of self-disclosure on Facebook [54]. Furthermore, Chen identified extroversion as “encourage[ing] users to reveal themselves online” [55]. Therefore, we propose:

H5: Extroversion is positively related to the user’s perception of CIS’ conditional value.

Figure 2: Summary of the hypotheses in the research model

Figure 2 shows the research model, and Table 1 contains the definitions of the constructs.

Table 1: Construct definitions		
Construct	Origin	Definition
Conditional Value	[41]	The value experienced in a certain context or situation based on the time or the user's location, social environment, technological environment, or mental state.
Disclosure Intention	[35]	The extent to which an individual expects to reveal his/her personal information to use a service.
Disclosure Value	[16]	The perceived utility of information disclosure based on perceptions of privacy risks incurred and benefits received.
Extroversion	[56]	A personality trait that is predominantly concerned with obtaining gratification from what is outside the self.
Privacy Risk	[20]	The concern that personal LBS data is misused.

Next, we add situational factors, which are not psychological constructs, as they emerge from specific contextual characteristics that influence the PCM.

3.2.1 Circle of Receivers of CIS information

Sharing one's location is a form of communication between a sender and at least one receiver [57]. Knowledge about "where someone has been, knowing what they are doing right now, and being able to predict where they might go next" can be powerful [58]. For example, the location of one's home, one's friends' homes, and the stores and entertainment venues one visits can "determine a great deal about an individual's beliefs, preferences and behavior" [59]. As a result, we contend that the circle of receivers—who receives one's location information—influences the CIS information disclosure intention. While the type and content of communication depends on the targeted receivers, individuals are likely to be more willing to share CIS data with a selected group of receivers (e.g., friends) than they are to share it publicly. Therefore, we state:

H6: CIS' perceived conditional value is greater when information is shared with selected receivers compared to being publicly shared.

3.2.2 Frequency of location visit

The perceived uniqueness of an event in which an individual visits a particular location at a particular time may also influence the intention to use CIS. Perceived uniqueness can be linked to an object's desirability by serving the meta-preference of defining oneself as distinct from others

[60]. In relation to CIS, we suggest that uniqueness has two components: the relevance of the location and the frequency with which the location is visited. Regarding the latter aspect we assume a diminishing marginal utility with increasing frequency. This is a common phenomenon in consumer research. For instance, first-time visitors in hotels are willing to pay more for a room with harbor view than repeat visitors as the perceived utility is higher [61]. We transfer these results in the context of CIS and state:

H7: CIS' perceived conditional value is greater when a location is rarely visited compared to being frequently visited.

3.2.3 Place relevance

Place relevance is the second component of uniqueness. Consumer research has indicated that the sensations derived from the experience of using products and services is an important factor in the consumer's attitude [62]. Furthermore, studies in social sciences and the humanities have also proposed that the user's mood in a specific context is critical to the use of CIS and the resulting sharing of location information [63]. Research has also confirmed that tourists ascribe personality attributes to places suggesting that places can differ in their hedonic nature [64]. For instance, the location of the stadium in which the individual watches a sports event can create excitement, increasing the conditional value, as the benefit of using a CIS to share an exciting location is greater than that of sharing a place with little excitement. Therefore, we propose:

H8: Perceived conditional value of a place is greater when a place with high relevance is visited compared to a place with low relevance.

4 Method

To examine the main drivers of CIS, we designed and conducted a true experiment (i.e., with random group assignment [65]) in a $2 \times 2 \times 2$ design with the three situational factors—circle of receivers, frequency of location visit, and place relevance—so eight groups resulted with group

sizes between 29 and 46 participants ($N = 296$). The experiment uses scenarios that describe possible future events, states, and intended behaviors [66]. Random assignment enables group compositions that are probabilistically similar, so any differences regarding the dependent variables can be attributed to the difference in the treatment that the groups received, not to differences in the groups' compositions [67]. The data analysis contains three separate methods (1). A PLS model with the outcome of "Disclosure Intention" that includes Hypotheses 1-5. (2). A group comparison using nonparametric comparisons of PLS unstandardized latent value scores that applies to Hypotheses 6-8. (3.) A post-hoc multi-group analysis (MGA) for control purposes.

4.1 Materials

We used measurement instruments from well-established constructs. Appendix A contains all items and the related constructs. The items were translated into German and then retranslated into English, which led to minor adjustments in the German translations. The scenarios were developed in a pre-study, following Maier, Wilken, Schneider and Kelemci Schneider [68] ranking approach. To determine *place relevance*, fifteen participants ranked twenty locations using a 7-point Likert scale. The scales were taken from Voss, Spangenberg and Grohmann [62]. From the evaluation of these scales, the three locations with the highest average ranking and the three with the lowest average ranking were selected for the manipulation of the place relevance (i.e., the hedonic nature of the context). Selected locations included the Club Space in Ibiza, Spain, (one of the top three locations) and a car park at the Cologne Cathedral, Germany, (one of the bottom three locations) (Figure 3).

Figure 3: Manipulations applied in the interface of the service

Place relevance was manipulated for the participants by displaying either high or low hedonic locations, while the frequency was manipulated by displaying the message, “This is your first check-in at this location” (low) or “Your last check-in at this location: 24 hours ago” (high). The circle of receivers was manipulated by sharing the check-in with either “public” (high) or with “friends” (low).

Descriptive data like age, gender, and education were also collected. Gender is particularly relevant to our study, as previous research has indicated ambivalent results: Schrammel, Köffel and Tscheligi [69] found that women were more cautious about revealing information than men were, while Hollenbaugh and Ferris observed no effect for gender in the case of self-disclosure via social networks [54]. These contrasting findings may have occurred because of the characteristics of the services under study, so we included gender as a control variable.

A pre-test was fielded to ensure content validity. Five researchers and fifteen students completed the survey and were given space for comments and suggestions that resulted in a refined task description, improved item formulations, and allowed the researcher to determine whether the randomization of the participants was effective.

4.2 Data collection

Data collection was carried out by means of a quantitative online questionnaire (Appendix A). A 10€ Amazon voucher for every fourth participant served as an incentive for completing the questionnaire. The questionnaire was administered online and was open to the participants for five weeks. A sample suitable for multiple group comparisons was collected by snowball sampling in Germany: a convenience sample included students recruited via their university email addresses, other young adults recruited via social networks, and targeted multipliers in these networks. Repetitive participation was prevented by means of an online tool that recognized recurring users and denied multiple attempts.

The survey started with an introduction to the study that contained a declaration of anonymity. Then the participants were asked about their demographics. Definitions of LBS and CIS were illustrated with exemplary use cases and icons of sample services. Thereafter, information regarding the use of CIS was collected along with the participants' perceptions of the associated privacy risks. Next, the participants were tasked with imagining that they were using the application in the circumstances displayed on a smartphone screen and to memorize the scenario. The online tool randomly placed the participants in one of the eight experimental groups and varied the application interface along the three factors of place relevance, frequency, and circle of receivers. Three mobile screen displays were shown with either the three top-rated locations or the three lowest-rated locations while frequency of location visits and circle of receivers remained constant in all three locations. Then, the participants assessed the constructs of the research model based on the given scenarios.

4.3 Participants

A total of 296 valid questionnaires were collected. To gauge whether the sample size was sufficient, we estimated the desired statistical power using G*Power 3.0 [70]. Given the sample size, expecting a moderate effect size (0.15), and an α error probability of 0.05, our experiment

design with eight groups and six response variables achieves a statistical power greater than 0.99 with a sample of 296, which is well above the suggested threshold of 0.8. The participants are almost equally distributed between men (48.0%) and women (52.0%). Most participants were between 25 and 29 years old (45.6%), followed by those between ages 18 and 24 (32.8%), those between ages 30 and 39 (18.9%), and those in other age groups (2.7%). The sample was highly educated, as 61.49 percent had obtained a university degree. While 80.7 percent of the respondents used LBS on their smartphones, only 41.9 percent used CIS. The participants took an average of about sixteen minutes to complete the survey. Of those continued after reading the introduction page, 74.6 percent finished the questionnaire. This high level of completion indicates high task involvement, and the low dropout rate suggests that the questions were perceived as understandable and meaningful.

Table 2: Respondent profiles	
Participants	
Questionnaire started	397
Questionnaire not finished; participant excluded	101
Final data sample used in the analyses	296
Gender	
Female	52.03% (154)
Male	47.97% (142)
Age (in years)	
under 18	1.01%
between 18 and 24	32.77%
between 25 and 29	45.61%
between 30 and 39	18.92%
over 40	1.69%
Highest level of education	
No degree	0.34%
High school degree	38.18%
University degree	61.49%

5 Results

We applied a structural equation modelling (SEM) approach using SmartPLS 3 [71] (in relation to H1-H5) as well as group comparison based on PLS unstandardized latent value scores using IBM SPSS 23 in order to test H6-H8 and to control for gender differences. Additionally, we

performed for control purposes a post-hoc multi-group analysis (MGA) in SmartPLS 3 to assess differences in the path coefficients across groups for gender and the three manipulations.

5.1 PLS results

5.1.1 Measurement Model

We assessed the quality of the measurement model based on indicator reliability, internal consistency, convergent, and discriminant validity [72, 73]. We measured *indicator reliability* by the factor loading, which should be above 0.7; factor loadings below 0.5 should be excluded from reflective measurement models [73]. In the applied model, apart from one indicator in extroversion (0.689), all factor loadings show values above 0.7. Indicator reliability is also demonstrated by low (lower than 0.7) cross-loadings with other indicators, which is the case for all the indicators. Consequently, the constructs achieve sufficient reliability.

Internal consistency can be ensured by calculating Cronbach's alpha, supplemented by composite reliability to address the limitations of Cronbach's alpha [72]. Cronbach's alpha is above the recommended threshold of 0.7 for all constructs, and composite reliability is in all cases above the recommended threshold of 0.6, so our data's internal consistency can be considered reliable. *Convergent validity* is determined if the average variance extracted (AVE) is above 0.5, as is the case for all of our constructs. *Discriminant validity* is determined when the constructs' cross-loadings are less than the loading on the main construct (Appendix B); when, based on the Fornell–Larcker criterion, the correlation of the latent variables does not exceed the square root of the AVE scores (Appendix C) [74]; and when the heterotrait-monotrait ratio of correlations (HTMT) for all constructs is below the most conservative threshold of 0.85 (Appendix D) [75]. All of these criteria consistently indicate that discriminant validity is given (see Appendix B-D).

5.2.2 Structural model

We estimated the structural model to examine our research model in terms of the significance for each hypothesized path and the explained variance for each dependent variable. After computing

the path coefficients in the structural model, we used bootstrapping to obtain the corresponding t-values (5,000 iterations). All hypotheses correspond to paths in the structural model. Each hypothesis test uses a path coefficient (positive or negative) and the statistical significance of the t-values. We assessed the 0.05, 0.01, and 0.001 significance levels in the t-tests [75].

Figure 4 shows the path coefficients. The research model explains 48.1 percent of the variance in disclosure intention. The positive relationships between conditional value and disclosure value (H1) and between disclosure value and disclosure intention (H2) are both supported. As expected, a negative relationship emerges between perceived risk and conditional value (H3) and between perceived risk and disclosure value (H4), so both hypotheses are supported. Extroversion is positively associated with conditional value, which supports H5. However, extroversion and perceived privacy risk can only explain 7.0% of the variance in conditional value suggesting that other factors influence this latent variable.

Figure 4: Results of the structural model (*** $p < 0.001$; ** $p < 0.01$).

5.2 Results of the group comparison

Next, we compared the unstandardized latent variable scores using the nonparametric Mann-Whitney U test. H6 speculated that the perceived conditional value is greater with a selected group of receivers than it is with a public group of receivers. However, while the participants with the selected receivers express a higher conditional value (3.89) than those with public receivers (3.64), the group differences are not significant ($U = 9,850$, $p = .150$), so H6 is rejected. Next, we examined the group differences in relation to the frequency of location visit. The mean of conditional value is 3.94 in the low-frequency group, compared to 3.62 in the high-frequency

group; since this differences is statistically significant ($U = 9,312$, $p = .031$), H7 is supported. The third manipulation addressed the location. We proposed that a location with high place relevance has higher conditional value than does a location with low place relevance. The mean of conditional value is 3.97 for the group that saw locations with high place relevance, compared to 3.57 for the group that saw locations with low place relevance. Since the difference is statistically significant ($U = 9,124$, $p = .016$) between the group that saw a location with high place relevance (mean rank = 137.38) and the group that saw a location with low place relevance (mean rank = 161.40), H8 is supported. Finally, we controlled for the possibility that gender influences conditional value and found that, while female participants have a higher mean score (3.84 compared to 3.67), this difference is not significant ($U = 10,162.5$, $p = .294$). Table 3 summarizes the results.

Table 3: Comparison of unstandardized latent variables scores across treatments								
Conditional value	Circle of receivers (H6)		Frequency (H7)		Place relevance (H8)		Gender	
	Selected (N=140)	Public (N=156)	Low (N=137)	High (N=159)	Low (N=159)	High (N=137)	Male (N=142)	Female (N=154)
Mean	3.89	3.64	3.94	3.62	3.57	3.97	3.67	3.84
Mean rank	156.14	141.64	160.03	138.57	137.38	161.40	143.07	153.51
U value	9,850.0		9,312.0		9,124.0		10,162.5	
p value	0.145		0.031		0.016		0.294	

5.3 Post-hoc PLS multi-group comparison

In the last part of our analysis we performed a PLS multi-group comparison (MGA), which was also based on a nonparametric Mann–Whitney U test; however, it compares path coefficients and adjusted R²s of the endogenous latent variables between the various groups [76]. Again we separated the sample based on the treatment (circle of receivers, frequency, place relevance, and gender for control purposes). Table 4 provides a summary of the results.

Table 4: PLS-MGA Multi group comparison results (* p < 0.05)								
Path coefficient/ adj. R ²	Circle of receivers		Frequency		Place relevance		Gender	
	Selected (N=140)	Public (N=156)	Low (N=137)	High (N=159)	Low (N=159)	High (N=137)	Male (N=142)	Female (N=154)
EV → CV	.153	.144	.127	.257	.138	.206	.203	.136
PR → CV	-.232	-.218	-.229	-.224	-.192	-.231	-.199	-.276
CV (adj. R ²)	.082	.064	.067	.114	.054	.098	.075	.096
CV → DV	.620	.543	.587	.570	.583	.583	.575	.589
PR → DV	-.237	-.346	-.338	-.261	-.296	-.293	-.323	-.277
DV (adj. R ²)	.511	.492	.549	.460	.492	.507	.501	.514
DV → DI	.748*	.638*	.724	.664	.611*	.774*	.751*	.640*
DI (adj. R ²)	.559	.407	.525	.441	.373	.598	.564	.409
EV = Extroversion; CV = Conditional value; PR = Privacy risk; DV = Disclosure value; DI=Disclosure intention.								

The results suggest that only the path coefficient between disclosure value and disclosure intention differs significantly between the groups. While the path coefficient is 0.748 in the group with a selected circle of receivers, the effect is 0.638 in the group with a public set of receivers, so the difference is significant. The path coefficient is also significantly higher in the group with the high place relevance (0.774) compared to the group with the low place relevance (0.611) and in the males (0.751) compared to the females (0.640). However, no significant differences emerge between the group that shared information rarely and the group that did so frequently (0.724 compared to 0.664).

Figure 5: Illustration of combined significant findings from all three methods (* PLS-MGA compares the entire PLS model but only the significant results are highlighted)

6. Discussion

6.1 Summary of Results

We set out to study eight hypotheses about conditional value of CIS in the PCM, the influence of situational factors, and the related CIS information disclosure intention. Table 5 summarizes the insights gained based on our hypotheses.

Table 6 : Summarized results		
No.	Hypothesis	Result
H1	A CIS' perceived conditional value is positively related to the perceived disclosure value of the CIS' information.	Supported
H2	The perceived value of a CIS' information disclosure, is positively related to the user's intention to disclose.	Supported
H3	Perceived privacy risk is negatively related to a CIS' conditional value.	Supported
H4	Perceived privacy risk is negatively related to the disclosure value of CIS.	Supported
H5	Extroversion is positively related to the user's perception of CIS' conditional value.	Supported
H6	CIS' perceived conditional value is greater when information is shared with selected receivers compared to being publicly shared.	Rejected
H7	CIS' perceived conditional value is greater when a location is rarely visited compared to being frequently visited.	Supported
H8	Perceived conditional value of a place is greater when a place with high relevance is visited compared to a place with low relevance.	Supported

The results support all hypotheses tested using structural equation modelling (H1-H5), and the group comparison suggests that two situational factors (frequency of location visit and place relevance) influence conditional value (H7, H8). However, we found no support for the influence of the circle of receivers on conditional value (H6). The results of the explorative post hoc analysis show an additional moderating influence of the circle of receivers, place relevance, and gender on the relationship between disclosure value and the intention to disclose location information, but no such influence for frequency.

6.2 Implications for Research

This study provides valuable insights into the role of conditional value and its effect on the CIS information disclosure intention. In addressing the first research question, we explored how conditional value can be used in the PCM. The study introduces a dynamic concept of value that changes based on the context and integrates this concept into the theoretical frame of the PCM. This effort extends previous attempts that have used a static concept of benefit that is independent of time and place in the calculus with privacy risks. The results confirm that privacy risk influences disclosure value in the PCM directly, as well as indirectly through conditional value. Both relationships reduce the intention to disclose CIS information. As for the second research question, we focused on the effect of situational factors on conditional value and CIS information disclosure and found that, in addition to the individual factor of extroversion, the situational factors of frequency and place relevance contribute directly to conditional value. In addition, our ex-post analysis suggests a moderating effect between disclosure value and disclosure intention, so we conclude that situational factors have two separate effects that affect the likelihood to disclose personal information in CIS. While their effect on conditional value can be explained with the specific value proposition of LBS and the PCM, PCM cannot explain the moderating effect that emerged in the post hoc analysis. As PCM follows a sequential structure, it appears that situational factors are considered twice: directly at the beginning of PCM and again at the end of our research model, when the disclosure value results in disclosure intention. PCM

assumes a rational assessment of risk and benefits, but this rational decision process should be completed after the disclosure value is determined. This result leads to the question concerning whether the moderating effect is also part of rational reasoning or if this decision making is done intuitively. A possible explanation that should be examined in future research could lie in the dual process theory of information processing that postulates two modes of thinking [77]: one that is conscious, slow and analytic, and one that is automatic, fast and intuitive [78]. In this context, future work could also combine our findings with Keith, Thompson, Hale and Greer [79], who applied heuristics to decision-making in the use of LBS, to determine whether situational factors influence both analytical information processing, resulting in conditional value and disclosure value, and an intuitive competent that acts as a moderator in the decision to disclose personal information. Our results emphasize the importance of situational factors in relation to CIS disclosure intention and could stimulate further theoretical conceptualization.

Additionally, our results confirm previous results from Schrammel et al. [69] in relation to CIS suggesting that women are more reluctant to disclosure information. A possible explanation is that CIS is a means of short communication, which is more likely to be preferred by men [80]. Our study also contributes to the body of acceptance research, as it uses a true experimental research design to determine the influence of these situational factors. The random group allocation and the three treatments allow us to measure group differences and to overcome a common limitation of acceptance research that is based on correlations between self-assessed variables. We show that the variables and the correlations can be manipulated through the scenario using situations displayed in a mobile app. Therefore, our results raise questions regarding the robustness of other studies examining intentional user behavior in relation to LBS. Future research should explore how alternative approaches can explain intentional and actual user behavior in scenarios with various situational settings.

6.3 Implications for Practice

The results focus on decision support systems that require data from users who do not benefit directly from the decision support. To use a CIS like Foursquare for location recommendations, others must have shared data voluntarily without receiving decision support. While data may also be collected later from users who followed recommendations, the motivations of users who share new locations are central to expanding the available information. Practitioners gain rich information about how risks and benefits result in a specific situation's disclosure value and eventually in disclosure intention.

We derived several recommendations for practitioners. First, practitioners can work to reduce their customers' perceptions of privacy risk by, for instance, integrating features into the service that reduce the risk or adapting how the service is presented to reassure consumers of its safety. CIS providers could communicate these features to potential users to reduce their perceptions of risk. Second, service providers can work to improve the conditional value by providing features that restrict the circle of receivers, perhaps by default, while providing incentives to change the settings and share more CIS information publicly. Third, the influence of place relevance could be used by CIS providers to encourage new users to disclose initially data about locations with a high hedonic nature (e.g., tourist attractions). Place relevance appears particularly suitable for manipulating information disclosure intention, as it has a direct effect on conditional value and a moderating effect on disclosure intention. Fourth, insights into users' characteristics can be used to target potential clients, such as extroverts by, for instance, suggesting default settings that disclose more personal information. Fifth, based on the moderating effect of the situational factor, frequency of location visits, on the relationship between disclosure value and disclosure intention, we recommend that practitioners develop a feature that controls the frequency with which information is disclosed for places that are visited on a regular basis. One setting could be to disclose information only at new places that the user has not visited before, and another could be to select time intervals, such as one check-in per week or per month. Sixth, the identified gender

differences could be used to provide different default settings for each gender based on the users' gender identification. Those who identify as male are more likely to disclose personal information than those who identify as female are, so their default settings could be set up less restrictively.

6.4 Limitations and future research

The study has several limitations. First, we focused on CIS as one kind of LBS, but the transferability of our results to other application areas of LBS may be limited. Second, one must consider the sample's composition before generalizing the study's findings. As the data collection took place online, it is likely that the respondents are reasonably well trained in technology, which may not be the case for the general population. Moreover, the data collection was restricted to Germany, limiting the findings' external validity. Third, the use of a scenario-based methodology is common in acceptance research, but it sets boundaries for our work's validity. Imagining scenarios is, by definition, simplifying the real-world context in which behaviors and decisions actually manifest. The intention to disclose information serves as an indicator of actual behavior but intentions and behavior do not always align. Fourth, we omitted known factors related to IS adoption. While we included some individual and situational constructs and benefits and risks, to focus on new factors we did not include other variables, such as perceived ease of use and social norms, that are known to explain acceptance. It is also possible that the constructs we used interact with these well-known factors. Fifth, the post hoc analysis in section 5.3 is explorative and goes beyond our theoretically derived research model. Further research is required to address these limitations.

Our findings also provide a foundation for future research on decision-making in relation to LBS information disclosure and the underlying rational and intuitive mechanisms (section 6.3). The study should also be expanded to include other cultures, as culture has been found to affect design and adoption decisions [81, 82]. In addition, incentives that are based on gaming or rewards may be value-enhancing features that could be incorporated in future studies to increase conditional

value. Examples such as Geocaching, Ingress, and Pokémon Go⁵ indicate the wide interest in location-based gaming. However, they also indicate that the interest in specific games and gaming aspects can be temporal. Future studies should examine if and for how long gaming incentives to share CIS information can increase the conditional value. Another stream of research could build on this study's findings and compare the results with actual user data (e.g., check-ins from Facebook or Foursquare) using a large-scale sample. The study could also be replicated by analyzing actual CIS data, which would control for actual user behavior. Future research should explore further drivers of LBS's conditional value in more detail, including the influence of individual factors like educational background.

7. Conclusion

Platforms like Foursquare provide recommendation systems based on the community. This study explored why individuals who do not directly benefit from such recommendation systems disclose CIS data that combines location, time, and identity information. Our intention was to explore the unique value propositions that emerge in a particular context and used conditional value as a dynamic concept of value that can change by the moment. We used this approach as an extension of PCM to explain the disclosure intention of personal information in relation to CIS. We then extended this model using a true experimental setting to identify the situational factors that influence conditional value. The results confirm the relevance of conditional value to PCM and determine two different ways how situational factors influence the disclosure intention. While frequency and location relevance have a direct influence on the conditional value, we also identify a moderating effect of the circle of receivers and location relevance on the relation between disclosure value and disclosure intention. The results pave the way for future research on the individual and situational factors that influence the conditional value of LBS and the decision to share LBS data on social media. Additionally, CIS depend on voluntary information disclosure

⁵ <https://www.pokemongo.com>, <https://www.ingress.com>, <https://www.geocaching.com>

and our results can be used to guide CIS providers to consider situational factors in order to increase the willingness of their users to share CIS information.

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Appendix A: Measurement instrument

All questions were asked based on the particular treatment displayed on the screen (circle of receivers, frequency of location visit, place relevance; see Figure 3). On the top of the page it was written: “Please answer all questions based on the previously displayed situation”. Additionally,

in front of each question battery it was stated: “Please indicate how far you agree with the statements based on the previously displayed situation”.

Construct (reference)	Loadings	Composite reliability	AVE	Cronbach's Alpha
Perceived privacy risk [20] (In my opinion . . .)		0.888	0.666	0.834
PR1: . . . I have to reveal too much personal data in order to make proper use of Check-In Services.	0.847			
PR2: . . . it is very easy for third parties to obtain unauthorized access to my personal data, if I use Check-In Services.	0.873			
PR3: . . . there is a threat that providers of Check-In Services abuse my data for advertisement.	0.808			
PR4: . . . the use of Check-In Services is associated with a higher risk of fraud than other mobile apps.	0.730			
Extroversion [83]		0.836	0.631	0.701
EV1: I like to be the centre of attention	0.822			
EV2: I will usually show off if I get the chance	0.862			
EV3: I want to amount to something in the eyes of the world	0.689			
Disclosure value [16]		0.906	0.842	0.941
DV1: I think my benefits gained from the use of Check-In Services can offset the risks of my information disclosure.	0.892			
DV2: The value I gain from use of Check-In Services is worth the information I give away.	0.936			
DV3: I think the risks of my information disclosure will be greater than the benefits gained from the use of Check-In Services. (reverse scale)	0.923			
Disclosure Intention [35] (Specify the extent to which you would reveal your personal information to use Check-In Services.)		0.947	0.857	0.916
DI1: Willing/unwilling	0.932			
DI2: Unlikely/likely	0.927			
DI3: Not probable/probable	0.918			
Conditional value [41]		0.891	0.731	0.816
CV1: I value this service, with the help of which I get what I need in a certain situation.	0.862			
CV2: I value the independence of place and time offered by the use of Check-In apps.	0.876			
CV3: I value the real time information and interaction that Check-In apps make possible.	0.826			

Appendix B: Cross Loadings

	Conditional value	Disclosure Intention	Disclosure Value	Extroversion	Privacy Risk
CV1	0.861	0.511	0.570	0.128	-0.211
CV2	0.876	0.480	0.570	0.125	-0.217
CV3	0.828	0.421	0.515	0.121	-0.128
DI1	0.472	0.932	0.671	0.067	-0.357

DI2	0.542	0.927	0.615	0.071	-0.278
DI3	0.523	0.918	0.638	0.102	-0.277
DV1	0.594	0.570	0.892	0.081	-0.370
DV2	0.618	0.686	0.936	0.084	-0.358
DV3	0.567	0.649	0.923	0.056	-0.434
EV1	0.108	0.069	0.073	0.822	-0.009
EV2	0.120	0.057	0.038	0.862	-0.030
EV3	0.118	0.079	0.081	0.690	0.044
PR1	-0.243	-0.321	-0.425	-0.007	0.847
PR2	-0.134	-0.234	-0.335	0.040	0.873
PR3	-0.161	-0.278	-0.325	0.011	0.808
PR4	-0.156	-0.223	-0.257	-0.040	0.730

Appendix C: Fornell Larcker criterion (construct correlation and square root AVE score)

	Conditional Value	Disclosure Intention	Disclosure Value	Extroversion	Perceived Risk
Conditional Value	0.855				
Disclosure Intention	0.552	0.926			
Disclosure Value	0.646	0.694	0.918		
Extroversion	0.146	0.086	0.080	0.794	
Perceived Risk	-0.220	-0.330	-0.422	0.002	0.816

Appendix D: Heterotrait-monotrait ratio of correlations (HTMT)

	Conditional Value	Disclosure Value	Disclosure Intention	Extroversion
Disclosure Value	0.751			
Disclosure Intention	0.638	0.758		
Extroversion	0.193	0.103	0.108	
Perceived Risk	0.254	0.473	0.368	0.067