EXTENDING UTAUT2 TO EXPLORE PERVASIVE INFORMATION SYSTEMS

Complete Research

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Abstract

The increasing emergence of pervasive information systems requires a clearer understanding of the underlying characteristics in relation to user acceptance. Based on the integration of UTAUT2 and three pervasiveness constructs, we derived a comprehensive research model to account for pervasive information systems. Data collected from 346 participants in an online survey was analyzed to test the developed model using structural equation modeling and taking into account multigroup analysis. The results confirm the applicability of the integrated UTAUT2 model to measure pervasiveness. Implications for research and practice are discussed together with future research opportunities.

Keywords: Pervasive Information Systems, Ubiquitous Computing, Smart Devices, UTAUT2, Structural Equation Modeling.

Introduction

"The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it" (Weiser, 1991). This statement paved the way for a new paradigm shift towards 'Ubiquitous Computing' (Weiser, 1991), 'Pervasive Computing' (Estrin et al., 2002; Saha and Mukherjee, 2003), 'Nomadic Computing' (Lyytinen and Yoo, 2002b), or the 'Internet of Things' (Ashton, 2009). All these concepts share the vision of a future world with everyday physical objects equipped with digital logic, sensors, and networking capabilities (Fleisch and Thiesse, 2007). The continuous and relentless technological progress will make these interconnected devices omnipresent, not least because of the miniaturization of microelectronic components together with a price decline due to advances in the development and manufacturing processes. This leads to a future vision, in which everything from aircraft engines through to toothbrushes will communicate in some form or another, dawning a new era, one in which today's internet gives way to tomorrow's Internet of Things (IoT). Today, we are in the middle of this paradigm shift, still facing a number of challenges. Among these is the enabling of full interoperability of interconnected devices by implementing uniform standards, allowing them a seamless automatic adaptation and autonomous behavior in all kinds of environments. The widespread employment of the IoT will also depend on mechanisms that ensure trust, security, and privacy, which are often challenging in their implementation (Miorandi et al., 2012). To name a single example, wireless communications must be secured against eavesdropping taking into account the constraint of low-power devices not capable of processing complex security mechanisms.

As an integral part of the IoT, pervasive information systems (PIS) will play an increasingly important role. In this context, PIS may be considered as the post-desktop era, in which smart devices act in a smart environment (Saha and Mukherjee, 2003). This transition towards PIS not only becomes evident with the recent emergence of smart devices in the media, such as smart glasses or watches, but also with the progressive extinction of so-called feature phones being replaced by smartphones. Even though the idea of PIS is not a new one, the IoT makes such systems increasingly useful as a consequence of a continuously improving network coverage and integrated internet services. However, success or failure of pervasive technologies highly depends on its users, which is why users' adoption is of paramount importance for establishing a widely used IoT. This gives rise to questions of how this kind of smart devices will be adopted by users and sustain in an IoT world.

It is against this background that the present study is concerned with the acceptance of PIS by end users. For this purpose, we consider the example of an everyday object such as Google Glass. Based on the integration of the extended 'Unified Theory of Acceptance and Use of Technology' (UTAUT2) proposed by Venkatesh et al. (2012) and the pervasiveness constructs proposed by Karaiskos (2009), we develop and empirically test a structural model for the explanation and prediction of users' intention to utilize a pervasive technology. This research contributes to the IS literature in that we investigate the applicability of the UTAUT2 model extended by the pervasiveness perspective to the domain of PIS and confirm its explanatory power for a new class of pervasive IT artifacts.

The remainder of the paper is organized as follows. In section 2, we first provide an overview of the concept of PIS and smart wearables, particularly Google Glass, together with a review of related work on technology acceptance and pervasiveness on which our study is based. This review guides the development of our research model followed by the formation of a set of hypotheses to be tested in section 3. Subsequently, we describe our research methodology in section 4 before we present the data analysis process and results in section 5. The paper concludes with section 6, in which we provide a discussion of our results and suggestions for further research together with a summary of our findings.

2 Related work

2.1 Pervasive Information Systems

The term 'Pervasive Information Systems' is still scattered across different research streams covering aspects of technology and management. Most of the related research disciplines are considering their research from an engineering perspective, thus they predominantly focus on the technological capabilities and technology-driven output of pervasive IT artifacts. However, the inclusion of applications and services allows for taking a broader view of PIS. In this context, Kourouthanassis and Giaglis (2008) provide a definition for PIS as "interconnected technological artifacts diffused in their surrounding environment, which work together to sense, process, store, and communicate information ubiquitously and unobtrusively support their users' objectives and tasks in a context-aware manner." Birnbaum (1997) was among the first who put technology in the rear and pointed out that future information systems must be capable of hiding their own complexity and providing invisible interfaces. He termed those systems 'Pervasive Information Systems', which are distinct from traditional information systems in certain aspects, i.e. the notion of user interaction and connectedness within a smart space become important. Hence, services built on an information systems platform are the key at which customers experience pervasiveness. Kourouthanassis et al. (2007) describe the differences between traditional desktop information systems and PIS in that they define the latter as systems which deal with non-traditional computing devices that seamlessly bind the digital with the physical environment and become one unit in the user's perspective. As a result, emerging pervasive IT artifacts forming part of PIS induce a new user experience and are thus of particular interest for research of technology acceptance.

The PIS considered in our study is the pervasive IT artifact Google Glass together with its capabilities of providing applications and services. It is a web-enabled wearable computer with an optical headmounted display that is intended to decrease user attention significantly when performing certain tasks. One of its main advantages is the capability of performing microinteractions – an interaction that gets the user in and out as quickly as possible by using appropriate interfaces (Starner, 2013). As compared to smartphones, Google Glass users have virtually immediate access to their applications since it is worn on the head and is always ready for use with an always-on connectivity. Smartphones are typically carried in a pocket or bag which delays the performance of a task as it must be taken out before it is ready for use. Furthermore, Google Glass provides continuous access to a variety of known services, be it emails or social networks, with the novel control concept of natural language voice commands. In summary, Google Glass and its capabilities includes the important characteristics of a PIS so that it fits perfectly in our research context.

2.2 Technology Acceptance and Pervasiveness

Over more than two decades, the field of individual-level technology adoption and acceptance has attracted numerous researchers among the information systems (IS) community (Venkatesh et al., 2007). In this context, the Unified Theory of Acceptance and Use of Technology (UTAUT) arose out of a synthesis of eight previous theories/models capturing the essential factors and contingencies to predict behavioral intention and actual use behavior predominantly in an organizational context (Venkatesh et al., 2003). UTAUT’s particular strength is its explanatory power, i.e. it is able to account for about 70 percent of the variance in behavioral intention to use a technology and about 50 percent of the variance in technology use, thus outperforming any of the eight constituent models. As such, it has been applied in a plethora of technology acceptance studies and proved to be valuable in enhancing our understanding of technology adoption (Venkatesh et al., 2012). In contrast to its predecessor, the extended UTAUT (UTAUT2) lays the focus on the consumer use context and includes three new constructs, these are: hedonic motivation, price value and habit (Venkatesh et al., 2012). Further modifications comprise the removal of the moderator voluntariness and a new relationship between facilitating conditions and behavioral intention. As compared to UTAUT, the variance explained of UTAUT2 remains considerable for both behavioral intention (adjusted R^2 of 74 percent) and technology use (adjusted R^2 of 52 percent).

The existing IT adoption models follow a general fashion to account for a large variety of IT/IS artifacts. However, the consequence of neglecting specificities of technology leads to a distorted perception of the multi-faceted IT artifacts available today (Orlikowski and Iacono, 2001). Emerging paradigms to which this holds true are pervasive/ubiquitous computing and PIS. In this respect, an early work from Garfield (2005) investigates the factors related to the use of a tablet PC and their impact on the acceptance within organizations by employing a qualitative field study. The results show that this type of IT artifact presents technical as well as organizational challenges to be addressed. Within the retail domain, the effects of PIS on user shopping experience were examined with the result that a number of dimensions were affected suggesting pervasive technologies to be integrated in customer shopping processes (Kourouthanassis et al., 2007). A further study considering PIS evaluated user acceptance of an RFID-based ticketing system by employing a lab experiment (Karaiskos et al., 2007). The theoretical constructs for this study were drawn from TAM and the innovation diffusion theory (IDT) along with constructs related to privacy and switching costs. The findings indicate that in accordance with other studies, usefulness and ease of use were the strongest predictors of behavioral intention.

A first attempt towards a technology acceptance model dedicated to pervasive technologies emerged from Connelly (2007), who named the developed model pervasive TAM (PTAM). The model consists in parts of the Technology Acceptance Model 2 (Venkatesh and Davis, 2000) and other models, while new constructs relevant to measure pervasiveness were added. However, the lack of measurement instruments for the new constructs leaves the model as a theoretical rather than an applicable contribution. This issue was addressed by Karaiskos (2009), who investigated technological characteristics of

PIS influencing technology adoption factors. His work not only comprises extensive development efforts to obtain valid measurement scales for three pervasiveness constructs, but also the validation thereof. Altogether, 16 items could be validated, each associated with one of three pervasiveness constructs: ubiquity, unobtrusiveness, and context awareness. He placed these constructs as antecedents of six predictors of behavioral intention in a research model and tested them using multiple regression analysis. The results show that the pervasiveness constructs have a direct effect on performance expectancy, effort expectancy, and perceived enjoyment while there is no or only a weak relationship with social influence, personal innovativeness, and perceived monetary value.

The literature described above reveals that only a few studies considered technology acceptance in the light of pervasive technologies. However, the growing number of this type of technology requires consideration in technology acceptance models. Against this background, we take the work in this area one step further in that we draw on the work from Karaiskos (2009) and integrate the pervasiveness constructs into the recently published UTAUT2. First, the predictors of behavioral intention used in Karaiskos (2009) and UTAUT2 are similar, as for which we assume compatibility. Second, the consumer context of UTAUT2 makes this model appropriate to test it in relation to Google Glass, which is primarily intended for end consumers and fulfills the requirements of a pervasive technology. Third, we integrate moderators in the relationships between the pervasiveness constructs and the key constructs influencing behavioral intention in UTAUT2.

3 Research model and hypotheses

Based on the integration of UTAUT2 and the three pervasiveness constructs proposed by Karaiskos (2009), we developed and empirically tested a structural model for the explanation and prediction of users' intention to use a pervasive technology such as Google Glass. The associated research model is depicted in Figure 1. It shows the pervasiveness-related constructs on the left side which effect the segment of UTAUT2 considered in our study on the right side.

In line with UTAUT2, we link the constructs performance expectancy, effort expectancy, social influence, hedonic motivation, and price value to behavioral intention. We only hypothesize the relationships between the pervasiveness constructs and the UTAUT2 constructs since the relationships on the part of UTAUT2 have been tested in several other studies. Besides, we do not test for all potential relationships between the pervasiveness constructs and the UTAUT2 constructs. Most of the relationships were taken from the results of the regression analysis from Karaiskos (2009) with only a few changes.

To adjust the UTAUT2 model to our research setting, we made the following modifications to the original model. First, we removed the construct use behavior. At the time of the survey, the regarded technological device in the study, Google Glass, was only available as a prototype to developers, which made it impossible for the survey participants to test or use it. Nevertheless, we retained behavioral intention as a good predictor of actual behavior (Ajzen, 1991; Sheppard et al., 1988). This approach is employed in many other studies (e.g. Thong et al. 2011). Second, we removed the construct habit. Having this construct in our research model would require the survey participants to use Google Glass for a reasonable period of time. Third, we removed the construct facilitating conditions as it lead to issues in the measurement model so that validity was violated. A further explanation is provided when the measurement model is discussed. Fourth, we added the pervasiveness constructs ubiquity, unobtrusiveness, and context awareness as antecedents to the independent variables of UTAUT2. This is also supported by Davis (1993), who states that system design features have an indirect effect on attitude towards using a technology. Fifth, we added the moderators experience and age that influence the relationships between pervasiveness constructs on the one hand and performance expectancy and effort expectancy on the other hand. The moderator experience needs to be regarded in a broader sense, that is to say, there exists a number of for which we consider the moderator as a general experience with pervasive technologies.

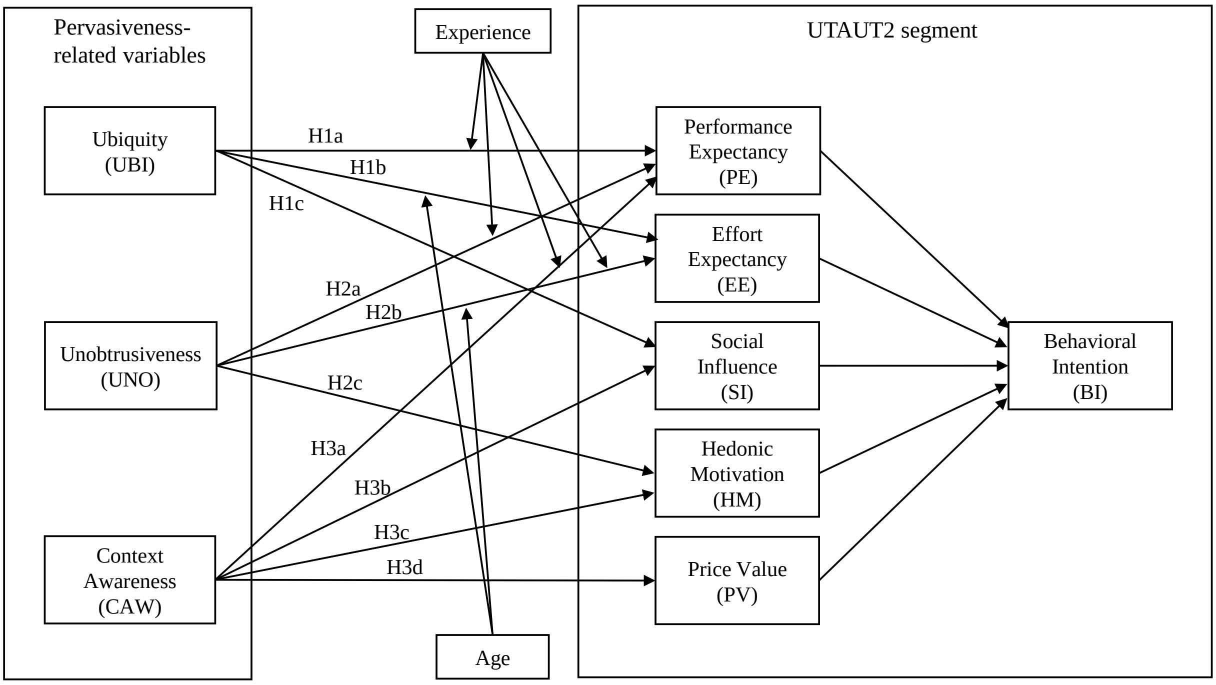

Figure 1. *Research model*

Ubiquity is the first pervasiveness construct we consider in our study. It is defined as "the system's capability to provide users with continuous access to information resources irrespective of their location within the system's boundaries" (Karaiskos, 2009). We expect ubiquity to positively influence performance expectancy and effort expectancy. This can be explained by a user's evaluation of task-technology-fit, which is defined as the degree to which a technology assists an individual in performing a task (Goodhue and Thompson, 1995). If a user has nearly always access to a technology, he or she is potentially always able to perform a task. For example, in case a user needs to reach a location without knowing the way, he or she may use a pervasive technology (e.g. smartphone) to provide him or her the directions to this location. However, the accessibility of a technology alone is not sufficient for performing a task effectively. Rather, the user needs to have some experience in using the services provided by a pervasive technology.

The continuous access to a pervasive technology might also positively impact effort expectancy. We assume that the user of a pervasive technology will find it easier to learn how to use the technology when he or she carries it with oneself the whole day. Especially in certain contexts, in which people experience 'dead time' (e.g. waiting or commuting) they might play with or test the technology's features. Further, this might depend on the age and the experience of the user. Younger people tend to deal with technologies in a different way as older people, i.e. they learn and use it in fluent and sophisticated ways (Vodanovich et al., 2010).

Finally, we expect ubiquity to positively impact social influence. This stands in contrast to Karaiskos (2009), who argues that technology factors only have a direct effect on those constructs that consider the system as object of evaluation. However, Thong et al. (2011) state that information and communication technologies and services are typically used to interact with a social environment in the consumer context. Google Glass features this kind of services and enables an individual to constantly stay in contact with his or her social environment. As a consequence, an individual might have a stronger effect on potential consumers suggesting an impact on social influence. Thus, we hypothesize:

H1a: The influence of ubiquity on performance expectancy will be moderated by experience, such that the positive effect is stronger among people with high experience.

H1b: The influence of ubiquity on effort expectancy will be moderated by age, such that the positive effect is stronger among younger people.

H1c: Ubiquity has a positive effect on social influence.

Unobtrusiveness is the second pervasiveness construct considered in our study. It is defined as the extent to which a system becomes both cognitively and physically invisible when using it (Karaiskos, 2009). We expect unobtrusiveness to positively influence performance expectancy, effort expectancy, and hedonic motivation. When performing a task with support of a pervasive technology, the task performance will increase the less a user is distracted (Lyytinen and Yoo, 2002a). This is of particular importance when a distraction can lead to safety issues as it might be the case when a user is driving a car. Technology over-fit, which negatively impacts task performance as a consequence of users being overwhelmed by features and functionalities (Junglas and Watson, 2003), might be an issue why experienced users cherish an unobtrusive pervasive technology.

Also, services provided by a pervasive technology contribute to effort expectancy if they are presented in an unobtrusive way to avoid overloading a user (Gil et al., 2011). Particularly, this holds for older people with low experience, since older people tend to have more difficulties in learning of new technologies (Morris et al., 2005). What’s more, it becomes an aggravating circumstance if they are distracted or overwhelmed by the way services are presented. A reinforcing effect might also be a lack of experience with the type of technology.

The technology should also minimize the distraction when invoking specific services, e.g. hedonic services. As Deng et al. (2010) show in their study, the perceived hedonic performance depends on the cognitive absorption. It might be positively influenced by an unobtrusive technology for which we assume unobtrusiveness to have a positive effect on hedonic motivation. This is also in line with the results from Karaiskos (2009) who found a weak but significant effect of unobtrusiveness on perceived enjoyment. Thus, we hypothesize:

H2a: The influence of unobtrusiveness on performance expectancy will be moderated by experience, such that the positive effect is stronger among people with high experience.

H2b: The influence of unobtrusiveness on effort expectancy will be moderated by age and experience, such that the positive effect is stronger among older people with low experience.

H2c: Unobtrusiveness has a positive effect on hedonic motivation.

Context awareness is the last pervasiveness construct in our study. It is defined as the degree to which a system is capable of processing contextual information to dynamically and proactively adapt its functionality and to provide relevant information/services to its user depending on the user’s task (Dey and Abowd, 1999; Karaiskos, 2009). We expect context awareness to positively influence performance expectancy, social influence, hedonic motivation, and price value. Following the definition of context awareness, task performance will increase in case a user is supported by relevant information or services to perform a task effectively. In this context, we assume that the more experience a user has with context-aware systems, the more efficient he or she will perform a task.

The assumption of context awareness impacting social influence contradicts again the assertion made by Karaiskos (2009) that technology factors only have a direct effect on those constructs that consider the system as object of evaluation. Despite that, his results in multiple regression show a significant positive effect of context awareness on social influence. In line with this result, we assume that services such as location-based services (LBS) as part of context awareness may have a positive impact on social influence. This can be explained by the dissemination of pervasive technologies supporting LBS and fostering the integration of social networking and pervasive computing (Rosi et al., 2011). For instance, Facebook and Twitter support the function of posting the user’s geo-location (e.g. while traveling) to share impressions or emotional state with his or her social environment. Furthermore, in a voluntary context social influence affects the perception about a technology with the mechanisms of internalization and identification (Venkatesh et al., 2003). Users of pervasive technologies providing functions that positively impact their social status gains might have a stronger impact on others who might believe they should use a pervasive technology in order to comply with their social environment.

At the same time, users experience enjoyment when using such functions that not only add utility, but also become part of the social communication (Barkhuus et al., 2008). Furthermore, context awareness is different from the other pervasiveness constructs in that it is a more tangible technology characteristic due to its functional nature. Thus, users might perceive context awareness as an enabling function for other services that provides an added value (e.g. through LBS) for which users might be willing to spend more money to increase the value for money of the technology. Thus, we hypothesize:

H3a: The influence of context awareness on performance expectancy will be moderated by experience, such that the positive effect is stronger among people with high experience.

H3b: Context awareness has a positive effect on social influence.

H3c: Context awareness has a positive effect on hedonic motivation.

H3d: Context awareness has a positive effect on price value.

4 Research methodology

4.1 Instrument development

The measurement scales for the constructs performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), and behavioral intention (BI) were drawn and adapted from Venkatesh et al. (2012), while those for the pervasiveness constructs — ubiquity (UBI), unobtrusiveness (UNO), and context awareness (CAW) — were drawn and adapted from Karaiskos (2009). The individual survey items were rated on a 7-point Likert scale ranging from “strongly disagree” to “strongly agree” (Appendix A). Concluding the survey, the participants were requested to answer three questions about social demographics, which included their gender, age, and experience. The latter was measured by asking the participants about their experience with smartphones (in years) as Google Glass was not available to the general public at the time of data collection. Hence, we substituted it with a common device that almost each participant was assumed to possess. Although it is not the stated Google Glass as in the context of our study, both share many aspects (e.g. smart device, similar applications) so that it can be assumed both can be used interchangeably in order to obtain data for experience with a general pervasive technology.

4.2 Data collection

Participant recruiting for the present study was conducted using the crowdsourcing platform Amazon Mechanical Turk (AMT). In order to ensure high data quality, we imposed participation requirements on our sample to be allowed to complete the survey. Notably, our decision to use AMT bases on the fact that the obtained data quality via AMT does not suffer in comparison to a laboratory experiment (Sprouse, 2011). Data collection was performed by using the open source survey application Limesurvey. At the beginning of the survey, the participants were instructed to read a short introduction about Google Glass. The text included information about the device’s characteristics, its possible areas of application, and information about the price range for the end-user version. Below the written information, we also included visual material in form of a figure and two short promotional videos. This introductory information about Google Glass was deemed to be sufficient to get acceptable responses from the participants.

A total of 353 complete responses was obtained, of which 346 were usable. The gender distribution revealed a more than twice as high percentage value for male than for female (67.6% vs. 32.4%). The sample's age ranged from 18-65 years with a mean age of 33 years (SD = 10.8), while 52% were equal or less than 30 years old. The experience with smartphones among our participants shows a mean value of 3.8 years (SD = 2.6), with 13.5% not possessing a smartphone, while the groups of 1-3 years and 4-6 years have the highest frequency with 32.1% and 44.1%, respectively.

N = 346	**Min**	**Max**	**Mean**	**Std. Dev.**
Age (years)	18	65	33.1	10.8
Experience (years)	0	15	3.8	2.6
Gender	68% Male, 32% Female			

Table 1. Sample demographics

5 Data analysis

This section describes the data analysis process and presents the results obtained from the study. The final dataset was analyzed using a two-step approach as analysis procedure of structural equation modeling (SEM), which estimates the measurement model and the structural model separately (Anderson and Gerbing, 1988). Instead of applying multiple regression analysis as it was done by Karaiskos (2009), we make use of covariance-based SEM (CB-SEM) in our study. This allows us to estimate a series of multiple regression equations simultaneously while integrating more than a single dependent variable in the research model (Hair et al., 2009). Furthermore, CB-SEM is recommended for the analysis of categorical moderators (Lowry and Gaskin, 2014).

5.1 Measurement model

A number of steps were taken prior to testing the structural model applying SPSS / AMOS 21 for the statistical data analysis. These include tests for reliability and construct validity, whereas the latter consists of the two subtypes of validity, namely, convergent and discriminant validity.

Since we draw on prior developed constructs, we started with verifying the fit of the internal structure of our model through the more rigorous validity criteria of a confirmatory factor analysis (CFA). Therefore, we checked for (1) reliability, (2) convergent validity, and (3) discriminant validity. Table 2 shows the values necessary for the subsequent reliability and validity checks. To demonstrate reliability, we examined the composite reliability (CR) for each construct for which we considered a cutoff-value of 0.7 (Bagozzi and Yi, 2011). All constructs showed a value above 0.7. Convergent validity is the extent to which different indicators that are designed to measure the same construct correlate with each other (Campbell and Fiske, 1959). It was established by examining the indicator reliability and the average variance extracted (AVE). First, we tested for indicator reliability by checking all squared standardized regression weights to be above 0.707. This threshold ensures that over a half of the variance is captured by the latent construct (Chin, 1998). All indicators had higher values than 0.707 except UNO4, UNO5, and FC1-4. Second, we calculated the AVE values for each construct. The AVE includes the variance of the indicators captured by their assigned construct relative to the total amount of variance. Constructs showing an AVE of less than 0.5 are subject to insufficient convergent validity. All constructs except FC exceeded the threshold value. Since FC revealed issues for convergent as well as item reliability we eventually decided to drop this construct that led to a purification of our scales. The individual indicator loadings for each construct are included in Appendix A.

Discriminant validity is the extent to which a construct discriminates from other constructs (Campbell and Fiske, 1959). This implies that a construct is able to account for more variance in the associated indicators than (1) measurement error or similar external, unmeasured influences; or (2) other constructs within the conceptual framework. If this is not the case, then the validity of the individual indicators and of the construct is questionable (Fornell and Larcker, 1981). Discriminant validity is supported if the AVE for each construct is greater than its shared variance with any other construct. Shared variance is the amount of variance that a construct is able to explain in another construct and is represented by the square of the correlation between any two constructs. Therefore, we calculated the maximum shared variance (MSV) representing the highest value for all shared variances that needs to be less than the AVE to suggest discriminant validity.

A measurement model invariance analysis is suggested when conducting a multigroup analysis (Steinmetz et al., 2008). This analysis tests if the factor structure is equivalent across different values of a multigroup moderator. Therefore, we tested for configural and metric invariance during the CFA to validate construct compatibility across groups (Vandenberg and Lance, 2000). Configural invariance is a crucial condition to be fulfilled for a model to be invariant across groups. It was determined by checking model fit for both moderator variables, age and experience, considering their respective groups. In both cases configural invariance could be obtained. Further, we tested for metric invariance for both moderators. A chi-square test revealed evidence of differences between their groups. Thus, the groups of the moderator variables age and experience were invariant.

To test for common method variance, we performed a Harman's single-factor test (Podsakoff and Organ, 1986). Factor analyses produced neither a single factor nor one general factor that accounted for the majority of the variance, indicating a low risk of common method bias.

	CR	AVE	MSV	PE	EE	SI	HM	PV	UBI	UNO	CAW	BI
PE	0.94	0.84	0.53	**0.91**								
EE	0.95	0.82	0.20	0.41	**0.90**							
SI	0.96	0.88	0.54	0.70	0.35	**0.94**						
HM	0.97	0.90	0.50	0.70	0.45	0.52	**0.95**					
PV	0.90	0.75	0.32	0.55	0.28	0.46	0.50	**0.87**				
UBI	0.95	0.84	0.53	0.52	0.38	0.40	0.38	0.38	**0.88**			
UNO	0.89	0.57	0.32	0.55	0.44	0.36	0.52	0.41	0.41	**0.76**		
CAW	0.92	0.69	0.50	0.53	0.39	0.46	0.49	0.43	0.50	0.71	**0.83**	
BI	0.95	0.88	0.54	0.73	0.44	0.73	0.67	0.56	0.57	0.52	0.52	**0.94**

Notes:
1. *PE — Performance Expectancy, EE — Effort Expectancy, SI — Social Influence, HM — Hedonic Motivation, PV — Price Value, UNO — Unobtrusiveness, UBI — Ubiquity, CAW — Context Awareness, BI — Behavioral Intention.*
2. *CR — Composite Reliability, AVE — Average Variance Extracted, MSV — Maximum Shared Variance.*
3. *Diagonal elements are the square roots of the AVE (in bold) and off-diagonal elements are correlations.*
4. *All correlations were significant at the p < 0.001 level.*

Table 2. Composite reliability, average variance extracted, maximum shared variance, and correlation matrix

5.2 Structural model

The overall fit measures were computed to assess the fit of our structural model to the data. The goodness-of-fit criteria used and their recommended cut-off values include χ^2/df < 2, TLI > 0.95, CFI > 0.95, SRMR < 0.08, and RMSEA < 0.06 (Hu and Bentler, 1999; MacKenzie et al., 2011). The results for our model are very close to or exceed these commonly accepted standards (χ^2/df = 1.986, TLI = 0.954, CFI = 0.959, SRMR = 0.080, RMSEA = 0.053), suggesting that the model provides an acceptable fit to the data. Figure 2 presents the structural relationships among the constructs and standardized path coefficients.

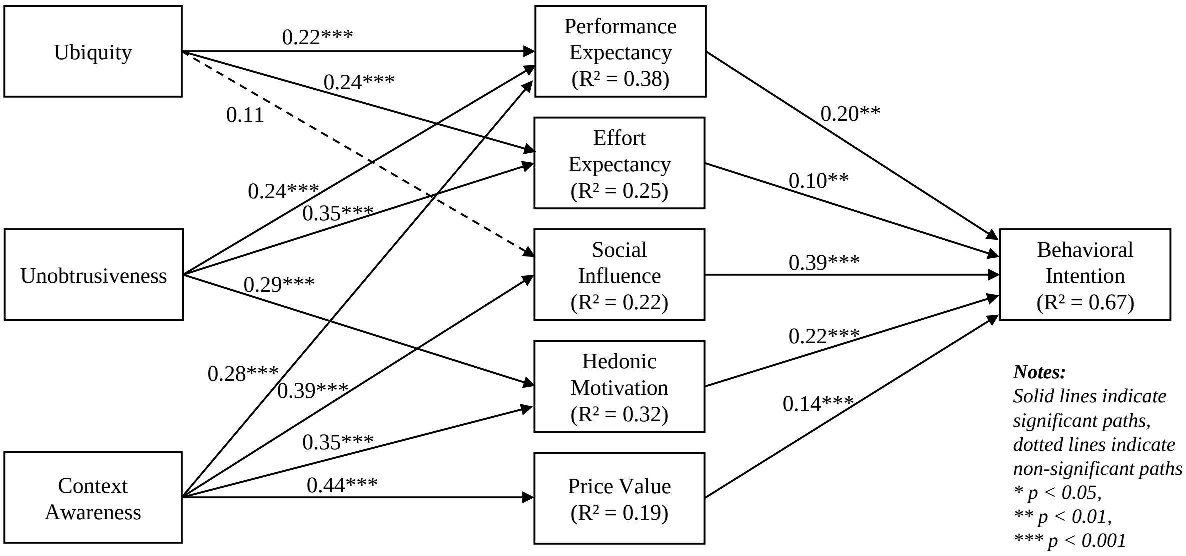

Figure 2. Structural model

The moderating effects of the categorical variables age and experience were examined by analyzing the differences of the respective groups. To test for the influence of age, we divided the data set into two groups: equal or less than 30 years (N=180) and more than 30 years (N=166). The two groups for experience were 1-4 years (N=154) and more than 4 years (N=140), while we excluded the group without experience. Table 3 shows the results of the moderating effects of both variables. The z-tests indicate if there are significant differences between the respective groups. The critical value for the z-test is +/- 1.645 at the 90% confidence level.

Moderator	**Group**	**UBI→PE**	**UBI→EE**	**UNO→PE**	**UNO→EE**	**CAW→PE**
None		0.22***	0.24***	0.24***	0.35***	0.28***
Age	≤ 30 years	0.30***	0.35***	0.19**	0.25**	0.32***
	> 30 years	0.06 (ns)	0.10 (ns)	0.32***	0.50***	0.30**
	z-test	**2.003****	**1.918***	-1.079 (ns)	**-2.288****	-0.06 (ns)
Experience	1-4 years	0.03 (ns)	0.17*	0.20**	0.40***	0.41***
	> 4 years	0.42***	0.35***	0.36***	0.27**	0.07 (ns)
	z-test	**-3.114*****	-0.78 (ns)	**-2.124****	1.386 (ns)	**2.181****

Notes: **** p < 0.001; ** p < 0.01; * p < 0.05; (ns): not significant*

Notes for z-test: **** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10; (ns): not significant*

Table 3. Moderating effects of the categorical variables age and experience

Table 4 summarizes the final results of the structural model. Nine out of the ten hypotheses were either partially or fully supported. In total, ubiquity showed weaker effects as compared to unobtrusiveness and context awareness. The path coefficient of the relationship UBI→PE was significant and also the moderating variable experience highlights significant differences between its groups providing support for hypothesis H1a. Interestingly, not only experience moderates the relationship, but also age, which was not part of the hypothesis. Further and according to H1b, we obtained a significant effect in the relationship UBI→EE moderated by age. H1c hypothesized a positive effect for the relationship UBI→SI, which could not be supported.

The relationships with unobtrusiveness reveal only significant effects. Hence, H2a was supported not least because the moderating effect of experience was significant. H2b was only partially supported since the path coefficient was significant, however, the hypothesized moderation was only significant for age but not for experience. H2c including the relationship UNO→HM could also be supported.

Finally, context awareness shows only significant and strong effects on SI, HM, and PV, thus supporting H3b, H3c, and H3d. In addition, H3a could be supported with the moderating effect of experience on the relationship CAW→PE.

Hypothesis	Relationship	Moderator(s)	Path coefficient	Result
H1a	UBI → PE	Experience	0.22***	Supported
H1b	UBI → EE	Age	0.24***	Supported
H1c	UBI → SI	None	0.11 (ns)	Not supported
H2a	UNO → PE	Experience	0.24***	Supported
H2b	UNO → EE	Experience, age	0.35***	Partially supported
H2c	UNO → HM	None	0.29***	Supported
H3a	CAW → PE	Experience	0.28***	Supported
H3b	CAW → SI	None	0.39***	Supported
H3c	CAW → HM	None	0.35***	Supported
H3d	CAW → PV	None	0.44***	Supported

Notes: **** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; (ns): not significant*

Table 4. Final results

6 Discussion and conclusions

Our research examined the factors that influence the adoption of pervasive technologies by using a modified UTAUT2 as a base model and extending it by three pervasiveness constructs, namely ubiquitiy, unobtrusiveness, and context awareness. We also accounted for the two moderator variables age and experience. Empirical analysis using CB-SEM confirmed the applicability of the integrated UTAUT2 model to measure pervasiveness in context of the pervasive technology Google Glass. Further contributions are as follows.

First, measurement model could confirm that the pervasiveness constructs have no issues in terms of reliability and construct validity. This validation might encourage other researchers in considering these constructs in their research. Second, the pervasiveness constructs developed by Karaiskos (2009) and the results from his multiple regression analysis supported our research in deriving the hypotheses. His results are in line with most of our results, except for the relationships UNO→PE and CAW→PV, for which he could not identify any significant effects but the corresponding hypotheses could be supported in our study. Third, our results show that not only experience but also age seem to influence the relationship UBI→PE. A possible reason might be that younger people consider technology more often for activities than older people do. This becomes apparent when one compares technology use for different activity types among these groups. Younger people tend to use their smartphone for a variety of activities, be it communication, information access, or time scheduling. In contrast, older people often prefer ‘offline’ activities or means such as meeting people, reading books or newspapers, or using a paper-based diary.

Regarding the three pervasiveness constructs, it can be stated that context awareness seems to be the most important characteristic for potential consumers of a pervasive technology. It defines a feature for which we could identify strong effects on the considered independent constructs of UTAUT2. In contrast, ubiquity and unobtrusiveness can be considered as important for performance expectancy and effort expectancy, while unobtrusiveness shows also a positive effect on hedonic motivation. It means a potential consumer cherishes ubiquity and unobtrusiveness of a pervasive technology as driver of improved effectiveness and efficiency in accomplishing tasks without becoming distracted from it.

Although it was not our primary focus, we discuss the direct effects on behavioral intention. In comparison with the results from UTAUT2, we can see that all predictors of behavioral intention reveal only minor deviations with the exception of SI, which has the strongest direct effect among all predictors of behavioral intention in our study. A probable reason therefore is a considerable mediating effect from context awareness to behavioral intention through social influence.

Besides the theoretical implications mentioned above, our study allows for drawing conclusions relevant to pervasive technology developers. First, we can argue that for the design and development of a pervasive technology all pervasiveness constructs should be considered. Second, we can observe that consumers cherish visible over invisible pervasiveness characteristics, that is to say, functional capabilities (context awareness) over system design characteristics (ubiquity and unobtrusiveness). Thus, we can conclude that it seems important to consumers that a pervasive technology incorporates context-aware services such as LBS. Third, ubiquity and unobtrusiveness remain important characteristics relevant to the utilitarian perspective, i.e. performance expectancy and effort expectancy. Ubiquity seems to be important to potential users in that they wish an omnipresent internet access, while unobtrusiveness is considered as being important in terms of distraction when performing a task. This implies that there is a trade-off between proactive applications that are intended to support the user and the way how these applications notify a user.

In summary, our research considers not only most of the constructs of UTAUT2 but also new constructs measuring pervasiveness of technology. We provided empirical support for the applicability of the integrated model via an online survey with 346 cases. In particular, context awareness had the strongest effects on all predictors of the UTAUT2 model considered in our study, while the other two showed significant but weaker effects. Our model accounts for 67% of the variance in behavioral intention, besides the pervasiveness constructs were able to explain a high percentage of variance in each independent variable in UTAUT2.

The present study comes with limitations that point to opportunities for further research. First of all, even though the size of our sample is large enough for testing our structural model, larger samples would be beneficial to additionally investigate the differences in adoption behavior between geographic regions and additional demographic factors such as income or education. Second, while having obtained sufficient explanatory power, our results nevertheless leave room for additional factors not included in our research model that might influence adoption behavior. In particular, the inclusion of the factors 'Facilitating Conditions' and 'Habit' would allow for a full integration of the pervasiveness constructs into UTAUT2. Third, the method of evaluating the moderator experience based on the usage in years might not reflect the actual experience with a pervasive technology. Finally, we propose to discuss and empirically test the relevance of privacy factors since those gain increasing importance among potential users of pervasive technologies.

Appendix A: Measurement items and loadings

Construct	Item	Loading	Statement
Performance Expectancy	PE1	0.90	I would find Google Glass useful in my daily life.
	PE2	0.93	Using Google Glass would help me to achieve things more quickly.
	PE3	0.91	Using Google Glass would increase my productivity.
Effort Expectancy	EE1	0.90	Learning how to use Google Glass would be easy for me.
	EE2	0.88	My interaction with Google Glass would be clear and understandable.
	EE3	0.94	I would find Google Glass easy to use.
	EE4	0.89	It would be easy for me to become skillful at using Google Glass.
Social Influence	SI1	0.93	People who are important to me would think that I should use Google Glass.
	SI2	0.93	People who influence my behavior would think that I should use Google Glass.
	SI3	0.95	People whose opinions that I value would prefer that I use Google Glass.
Facilitating Conditions *DROPPED*	FC1	0.56	I have the resources necessary to use Google Glass.
	FC2	0.81	I have the knowledge necessary to use Google Glass.
	FC3	0.73	Google Glass is compatible with other technologies I use.
	FC4	0.49	I can get help from others when I would have difficulties using Google Glass.
Hedonic Motivation	HM1	0.95	Using Google Glass would be fun.
	HM2	0.96	Using Google Glass would be enjoyable.
	HM3	0.94	Using Google Glass would be very entertaining.
Price Value	PV1	0.81	Google Glass is reasonably priced.
	PV2	0.97	Google Glass will be a good value for the money.
	PV3	0.81	At the future price Google Glass provides a good value.
Unobtru-siveness	UNO1	0.76	My attention would not need to be focused on Google Glass the whole time.
	UNO2	0.82	I would not have to concentrate fully on Google Glass when using it.
	UNO3	0.87	I would not need to be intensely absorbed when using Google Glass.
	UNO4	0.70	The usage of Google Glass would not disrupt me from other activities.
	UNO5	0.67	Google Glass would not distract me too often.
	UNO6	0.71	Google Glass would not require continuous attention.
Ubiquity	UBI1	0.84	Google Glass would be available to use wherever I need it.
	UBI2	0.82	Google Glass would be available to use whenever I need it.
	UBI3	0.92	I would be able to use Google Glass anytime.
	UBI4	0.93	Google Glass would be accessible everywhere in my daily life.
	UBI5	0.91	Google Glass would be always available to me.
Context Awareness	CAW1	0.80	Google Glass is able to adapt to changing conditions.
	CAW2	0.90	Google Glass can act according to the current circumstances.
	CAW3	0.90	The actions of Google Glass are in line with the situation.
	CAW4	0.80	Google Glass automatically adapts to the situation at hand.
	CAW5	0.75	Google Glass can automatically trigger actions relevant to the situation.
Behavioral Intention	BI1	0.90	I intend to use Google Glass in the future.
	BI2	0.94	I will always try to use Google Glass in my daily life.
	BI3	0.97	I plan to use Google Glass frequently.

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