Exploring the Acceptance of Ubiquitous Computing-based Information Services in Brick and Mortar Retail Environments

An Integration of UTAUT2 and Media System Dependency Theory

Vom Promotionsausschuss der

Technischen Universität Hamburg

zur Erlangung des akademischen Grades

Doktorin der Wirtschafts- und Sozialwissenschaften (Dr. rer. Pol.)

genehmigte Dissertation

von

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2018

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Tag der mündlichen Prüfung: 19.06.2018

Acknowledgment

Doing a PhD and writing a dissertation is an enjoyable and fulfilling but at the same time a long and rough journey; loaded with many moments of excitement and motivation but also that of exhaustion and disappointment. Without academic and emotional support of many people along this journey I wouldn't be able to successfully complete it.

First and foremost, with deep sense of gratitude, I wish to thank my advisor, Professor Thorsten Blecker, for his academic support, insightful discussions, and constructive criticism. I would also like to thank Professor Christian M. Ringle for accepting to be my second advisor. He was always generous with his time answering my questions and giving invaluable feedbacks on my work.

Even though this dissertation was a big milestone in completing my PhD, it might not do justice summarizing my experience at the Institute of Business Logistics and General Management (LOGU) of TUHH. My experience at LOGU was nothing short of amazing for which I am indebted to my great colleagues, faculty and staff of LOGU, many of whom became my true friends ever since we met at the institute. A special acknowledgment goes to my officemates: Semah Ibrahim Ben Abdelaziz and Ahmed Ziad Benleulmi whose support especially during survey design and data collection was invaluable.

In addition, I would like to thank Hella, Herman, and Thorsten who provided me with the best imaginable warm and inviting environment upon my arrival in Hamburg. Since my first day in Hamburg I have felt at home and since then they are like family to me.

Finally and most importantly, I am endlessly grateful to my family. I could not be the person I am today without them. My dear parents, Hamideh and Belal, unconditionally and generously supported me in every imaginable way to reach my dreams. They inspired me to love and enjoy learning, and taught me that it is only with persistence and hard work that one could achieve her dreams. My lovely sisters, Shirin, Solmaz, and Salma, and brothers, Mohammadhassan, and Khaled, were always there to motivate and cheer me up. Finally, my best friend and husband, Philipp, whom I cannot thank enough was an outstanding emotional support and a great academic advisor. He patiently listened to each and every one of my presentations, discussed

ideas, and shared the passion for research with me. I am eternally blessed to have him by my side.

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1 Introduction

1.1 Motivation

In 1973, Engel, Kollat and Blackwell introduced a high level customer behavior model based on the John Dewey's (1910) five-stage problem solving process. Since then this model has been the most accepted model in the customer behavior literature (Blackwell et al., 2005; Hawkins et al., 2003). As shown in Figure 1, the model divides customer decision making process into five core stages, namely need recognition, information search, alternative evaluation, purchase decision, and post-purchase behavior.

Figure 1: Engel-Kollat-Blackwell's consumer behavior model

For the purpose of this dissertation, the focus is on the information search and alternative evaluation stages. In these stages, customers search information on the alternatives and/or attributes of the alternatives they consider choosing and compare the various options to manage the perceived risk involved in a purchase decision (Payne et al., 1993). Information search and alternative evaluation and their impact on purchase choice have been a research focus of customer research for more than three decades (Bettman, 1979; Kivetz and Simonson, 2000; Levin et al., 2000; Srinivasan, 1990).

The interplay of the Internet technology and its ever increasing adaption has been the source of structural changes in different aspects of customer behavior, from the ways customers search for information to the ways they purchase products and communicate with companies or other customers (Hennig-Thurau et al., 2010; Klein and Ford, 2003; Libai et al., 2010; Mathwick and Rigdon, 2004; Shankar et al., 2011; Verhoef et al., 2007). Arguably, the information search and evaluation stages have undergone the most dramatic shifts (Grewal et al., 2013).

Difficulty (ease) in searching and finding products and product information at information search and evaluation stages results in negative (positive) shopping experience and consequently affects the choice of customers for their next purchase act (Kowatsch and Maass, 2010; Pantano and Servidio, 2012; Udo et al., 2010; Yoon and Kim, 2007). Unique characteristics of the Internet namely connectivity, interactivity (flexibility of choice in representing information), and access (speed of access, scope of access) enable customers to effectively and efficiently find, classify, and evaluate product information (Cook and Coupey, 1998; Kiang et al., 2000; Lehto et al., 2006; Peterson and Merino, 2003). Equipped with powerful retrieval techniques, the Internet makes the fast and convenient comparison and evaluation of a greater number of alternatives possible. The availability of detailed product information is found to be the most appealing feature of online shopping (Burke, 2002). Lower search costs and freedom from physical contact with sales staff among others elevate the Internet to the most favorable channel for information search and alternative evaluation (van Nierop et al., 2011).

In Germany, about 80% of the population use the Internet from which 63% use it daily (Frees and Koch, 2015). 76% of the Internet users employ the Internet to search for information about products and services, making information search the most favorable Internet-enabled service after sending and receiving emails (78%) (Frees and Koch, 2015). The trend of online information search threatens the competitiveness of the brick and mortar retail in two dimensions: namely loss of customers and loss of influence:

Loss of customer: research shows that the information search channel is a strong predictor of the choice of the purchase format (Cao, 2012; Cao et al., 2011; Schröder and Zaharia, 2008; Shim et al., 2000). That is customers tend to conduct the act of purchasing in the channel through which they search for and evaluate the product information. Therefore, the more people use the Internet for information search and evaluation, the more people purchase online which means loss of customers for brick and mortar retail (Shim et al., 2000). Based on a study by HDE[1] and Gfk[2]; the average growth of the offline retail industry in Germany has been only 0.2%, whereas this

[1] Handelsverband Deutschland e.V (German retail association) is the umbrella organization of German retailing for approximately 400,000 independent companies with around 3.0 million employees and more than 420 billion Euros annually in sales. The organization represents the interests of the retail industry in Germany and the European Union.

[2] **G**esellschaft **f**ür **K**onsumforschung SE (society for consumer research) is Germany's largest market research institute, and the fourth largest market research organization in the world.

number reaches to 12.2% for the online retail in the past ten years (*Handel digital: Online monitor 2014*, 2014). Having a closer look at the more recent developments in Germany, the nonfood online commerce captures all the gains in retail sales; in 2014 the nonfood online retail market experienced around 7% growth, whereas the offline retail market has become stagnant (*Handel digital: online monitor 2015*, 2015).

Loss of influence: the ultimate decision of purchasing or not purchasing is formed in the information search and evaluation stages, therefore it is crucial for retailers to be able to communicate with their customers in these stages. Based on a recent study published by PWC[3], 64% of German customers search for information online before purchasing in brick and mortar stores (Bovensiepen et al., 2015). The behavior pattern of search online and purchase offline leads to the loss of valuable information about customers and consequently the loss of influence on their decision making for brick and mortar retail (van Nierop et al., 2011); after all, understanding and engaging with an increasing number of customers who have their decision made or influenced outside the store is more challenging.

The experience of searching online has raised the bar for information services, today customers expect more easy-to-access, easy-to-evaluate and transparent information (Burke, 2010). Thus in today's highly competitive and multi-channel retail environment, a channel's capability to enable the customers to spot the relevant product information turns to be a decisive channel driver. As a result, the tendency of brick and mortar retailers to adopt new innovative technologies is growing, technologies which can gratify customers' rising demand for information services and support retailers to obtain precise and real-time information about market trends and shopping and selling processes (Bennett & Savani 2011; Fiorito et al. 2010; Shankar et al. 2011; Chen & Tsou 2012; Pantano & Viassone 2013). For example, information kiosks (Zielke et al., 2011), interactive displays, mobile shopping assistances (Resatsch et al., 2008; van der Heijden, 2006), and smart mirrors offer customers all in-store and sometimes complementary information in a similar way as the Internet does.

[3] **P**rice**w**aterhouse**C**oopers is the largest professional services firm in the world, and one of the Big Four accounting firms.

From the technological point of view, these technologies can be categorized under the concept of ubiquitous computing. Ubiquitous computing is characterized by integration of the computational resources into the physical environment to support users with customized services on demand (Weiser, 1991). Henceforth, the digital technologies (services) developed to assist the information search and evaluation of customers in brick and mortar retail will be referred to as in-store ubiquitous computing-based information technologies (services).

Based on the information system research, to effectively deploy and manage the information resources, companies should be able to answer two crucial questions: what is the value of information technology to the firm and what are the determinants of that value (Taylor and Todd, 1995a). Therefore, to ensure the successful implementation of in-store ubiquitous computing-based information technologies, retailers need to have a clear understanding about the benefits of such technologies as well as the customers' usage as a necessary condition for realization of those benefits.

1.2 Research Gap

Consistent with the common practice in information system research, two streams of research can be identified regarding the implementation of in-store ubiquitous computing information services: studies assessing the benefits of such technologies for retailers and studies examining the usage as a necessary condition for the realization of those benefits. However, as in-store ubiquitous computing-based services are relatively new, an overview of previous studies shows a rather skewed distribution of the literature with a penchant towards studying the benefits.

Various scholars investigated the benefits of implementing in-store ubiquitous computing technologies (e.g. Burke, 2002; Pantano, 2010a; Pantano and Naccarato, 2010; Renko and Druzijanic, 2014; Weber and Kantamneni, 2002). In general, the benefits can be summarized in two dimensions namely cost reduction and value creation:

Cost reduction: implementing ubiquitous computing technologies enables brick and mortar retail to reduce the interaction and communication costs with customers (Pantano and Naccarato, 2010). First of all, due to the self-service nature of ubiquitous computing systems, labor costs can be significantly saved (Bitner et al., 2002). Furthermore, through such digital technologies, brick and mortar retail can attain fast and precious digital information on customer behavior in the store. Similar to the online clickstream data, such information is valuable as they allow the prediction of market trends and the creation of personalized marketing and promotional programs along with the possibility to track their effectiveness (Kourouthanassis and Roussos, 2003; Pantano, 2014a; Pantano and Naccarato, 2010). In addition, these information can be used to eliminate out-of-shelf/out-of-stock conditions (Kourouthanassis and Roussos, 2003).

Value creation: augmenting stores by ubiquitous computing systems enables brick and mortar retail to increase and sustain the sales volume by leveraging the quality of services and thus customer experience (Bitner et al., 2002). Customers make their information channel choices based on their prior experience (Verhoef et al., 2009). Thus the better the experience, the higher the customer return rate. Furthermore, the more consumers enjoy their shopping experience, the likelier that they make purchases (Kim and Kim, 2008). Extending the convenience of online retail to offline retail, ubiquitous computing-based services enable an easier access to a large amount of information on products and an improved response time to customer requests (Zhu et al., 2013). In addition, such technologies can be used to directly target the service quality blockages, for example, unprepared frontline employees, low speed in responding customer requests and long queues resulting from limited human resources (Pantano and Migliarese, 2014). Due to the self-service nature of ubiquitous computing systems, customers can actively participate in service creation (Pantano and Migliarese, 2014). The possibility to be involved in service creation induces the feeling of autonomy and control, thus increasing customers' perception of service quality (Pantano and Migliarese, 2014). In addition, augmenting retail stores by ubiquitous computing systems modifies the appearance of stores in terms of style, layout, and atmosphere making them more appealing (Grewal et al., 2013; Pantano and Naccarato, 2010). As a consequence, there will be new elements capable of stimulating customers' attention and interest (Pantano and Di Pietro, 2012; Pantano and Naccarato, 2010; Poncin and Ben Mimoun, 2014); such elements can influence customers' shopping experience (Baker et al., 2002; Grewal et al., 2013; Pantano and Naccarato, 2010). In this regard, Pantano and Naccarato (2010) compare new in-store technologies with videogames: "*consumers can play with products as in a videogame, due to the high level of interactivity of technologies*" (p. 203). In today's connected world, the notion of customer experience gets an additional touch of importance; Grewal et al. (2013) perfectly illustrate this: "*in the old days, a bad shopping* *experience might have been shared with five to ten friends. Today, this reach extends to a customer's entire social network (…) and beyond if the customer chooses to share a bad experience on various blogs or through YouTube*". Building on the same logic, delivering a special and good experience would help the retailers to reach out to new customers.

The above-mentioned potential benefits of in-store ubiquitous computing-based services will not come into sight unless customers embrace and use them. Therefore, before implementing, retailers need to have a well-thought-out strategy to ensure the effectiveness of the design, choice, and introduction of the technologies into their stores. The building block for developing such strategy is to understand how customers will evaluate in-store ubiquitous computing-based services, how this evaluation contributes to their usage decision and if the usage indeed affects their future store choice.

Research on the usage of ubiquitous computing-based technologies has been a rather neglected issue and only recently addressed in few studies (Kowatsch et al., 2011; Kowatsch and Maass, 2010; Pantano and Di Pietro, 2012; Pantano and Viassone, 2012). Therefore, yet, little is known about how customers will actually evaluate these technologies. In her recent paper, Pantano (2014b) analyzes the retail innovation drivers particularly for in-store ubiquitous computing technologies, in her findings "*the uncertainty of consumers' reaction emerges as the most significant restraining force*" (p. 349) behind the implementation of such technologies. The reason that despite its potential benefits and introduction of various successful prototypes, the diffusion of ubiquitous computing-based services in retailing is still limited and discontinuous with a quite high heterogeneity of systems (Pantano, 2014b). Caceres and Friday (2012) address this issue emphasizing that to foster the way of ubiquitous computing technologies into the market, the future research should focus on the user in terms of "who" and "why". Addressing this research gap and responding to the call for research, the overarching question of this dissertation is:

What drives the usage of in-store ubiquitous computing-based information services?

Furthermore, it is important to examine if the usage of in-store ubiquitous computing-based services indeed results in the above-mentioned hypothetical benefits for retailers in terms of customer retention and acquisition. Thus another question which arises is:

Does the usage of in-store ubiquitous computing-based information services affect the customers' future store choice?

As discussed in the motivation section, the expanding trend of online information search challenges the competitiveness of brick and mortal retail and the introduction of in-store ubiquitous computing-based information services can help to deal with this challenge. However frequently claimed in the literature, to the best of the author's knowledge, there is neither a theoretical nor an empirical study examining this claim, therefore the question to be asked is:

Does and how the expanding trend of customers' online information search affect their evaluation of in-store ubiquitous computing-based information services?

Although interrelated, the information search and alternative evaluation stages are distinct in terms of needs. Rationally, in-store ubiquitous computing-based information services can be divided into two categories: services for information search and screening and services for alternative evaluation. As customers proceed in their decision making process, they stop to gather information about certain attributes and start to build a set of the most promising alternatives which then would be compared in more depth by processing bundles of product attributes and customer benefits (Payne et al., 1993, 1988). Therefore, in general the alternative evaluation stage is perceived as more complex than the information search stage (Payne et al., 1993, 1988). In addition, becoming closer to the purchase decision in this stage, the effect of possible undesirable consequences of a faulty choice is most comprehended by customers (Tversky and Kahneman, 1981). Therefore, customers may evaluate the assisting technologies for each of these stages differently. For example regarding the online technology, research shows that the online channel is more compatible with customers' needs in the information search stage than in the alternative evaluation stage; as by increasing complexity customers tend to seek expert or personal help in offline stores (Frambach et al., 2007). Regarding ubiquitous computing-based information services, to the best of author's knowledge, there is one single exploratory study addressing this issue; Karaatli et al. (2010) investigated the user perception of mobile based shopping assistance services at different stages of the consumer decision making process. Based on their findings, more customers believed that mobile services can improve their shopping experience in the information search stage than in the alternative evaluation stage.

However, they haven't addressed the potential effect of this perception on customers' technology evaluation and use. Therefore, the question to be asked is:

Do customers' evaluations of in-store ubiquitous computing-based information services differ for different pre-purchase stages (information search vs. alternative evaluation)?

Reviewing the current developments of in-store ubiquitous computing-based technologies, it becomes evident that different technologies have been developed to assist customers through the information search and alternative evaluation process. However heterogeneous, these in-store technologies can be divided in two main categories namely store-based systems (store owned devices) (Melià-Seguí et al., 2013; Pantano, 2010b; Pantano and Naccarato, 2010) and applications based on customers own smart mobile devices (Gao et al., 2010; Kowatsch et al., 2011; Kowatsch and Maass, 2010). As the level of investment in store-based systems is significantly higher than in mobile applications, it is important for retailers to know if customers perceive and evaluate these technologies differently. In this regard, Pantano (2014b) argues that, as current models fail to investigate the potential effect of technology type on customers' usage decisions, they are unable to provide retailers with a guideline on which is the best technology to invest in and calls for further research on this topic. Therefore, another question to be asked is:

Do customers' evaluations of in-store ubiquitous computing-based information services differ for different technology types (store-owned vs. user-owned)?

From the theoretical point of view, in the information system research a mature stream of research has been established which attempts to answer such questions. Referred to as technology acceptance research, this stream of research is dedicated to the psychology of the technology user and built on the grand theories of social psychology, such as the theory of reasoned action (TRA) (Fishbein, 1967) and theory of planned behavior (TPB) (Ajzen, 1985). These theories are designed to explain the human behavior taking a holistic approach and therefore can be also applied to the acceptance of technological innovations. Here, acceptance is defined as a consequence variable in "*a psychological process that users go through in making decisions about technology*" (Dillon and Morris, 1996, p. 13).

The first and most famous theoretical model in the field is the technology acceptance model (TAM) (Davis, 1986). TAM offers a unified set of constructs and indicators applicable for understanding and describing an individual's acceptance of information systems. Since its introduction, TAM has been one of the most influential models in information systems field and much of the technology acceptance studies are based on TAM or one of its various extensions (Lee et al., 2003; M. D. Williams et al., 2009).

However, generalizability in different contexts and settings is one of the important attributes of a theory, in the field of information system research, there has been a widely recognized need for context-specific theory development (e.g. Chiasson and Davidson, 2005; Orlikowski and Iacono, 2001; Rosemann and Vessey, 2008; Venkatesh et al., 2007). TAM can serve as the basis for technology acceptance studies, yet it needs to be refined and extended in regard to different information technologies as there is no one universal set of determinants which could explain the acceptance of all kind of technologies in any context (Adams et al., 1992; Davis, 1989; Davis et al., 1989). Not surprisingly, as a subfield of information systems research, the need for development of the context-specific theories is also recognized for the acceptance of ubiquitous computing technologies. In this regard, Yoon and Kim (2007) note that "*ubiquitous computing technology is seen as an emerging new information technology with such potency that it has changed the way we view IT. Although perceived ease of use and perceived usefulness constructs have been considered important in determining the individuals' acceptance and use of IT in the last few decades, factors contributing to the acceptance of a new IT are likely to vary according to the technological characteristics, the target users, and the context*" (p. 102). Furthermore, a recent literature review article of technology acceptance studies calls for the development of context specific models for the state of the art technologies as ubiquitous computing technologies (Chen et al., 2011).

Therefore, to address the above mentioned research gaps and questions, the objectives of this dissertation are

- developing a comprehensive and theoretically found model for the user acceptance of in-store ubiquitous computing-based information services to analyze the antecedents and consequences of the acceptance of such technologies,

- developing theory driven hypotheses on the influences of the expanding trend of customers' online information search on the user acceptance of in-store ubiquitous computing-based information services,
- empirically exploring the developed theoretical model for the user acceptance of in-store ubiquitous computing-based information services,
- empirically exploring the developed theoretical model for different service types (services for information search vs. alternative evaluation) in order to identify the stage specific determinants of user acceptance,
- empirically exploring the developed theoretical model for different technology types (store owned vs. user-owned), in order to identify the technology specific determinants of the user acceptance,
- and deriving managerial implications and recommendations for brick and mortar retail to increase the effectiveness of design, choice, and introduction strategies of in-store ubiquitous computing-based information systems.

1.3 Structure of the Thesis

To achieve the above mentioned research objectives, the key findings of relevant research in technology acceptance, consumer research and media effects have been combined to build a comprehensive model and develop theoretically found hypotheses for acceptance of ubiquitous computing-based information services. Based on the theoretical groundwork, in the empirical part, using primary data collected through a scenario-based online survey and applying the partial least squares structural equation modeling (PLS-SEM), both hypotheses-based and exploratory analyses have been conducted. The results of these analyses then form the basis for the derivation of recommendations for implementation of ubiquitous computing-based information services. This procedure is elaborated below:

To specify the under scrutiny technology, the concept of ubiquitous computing and the current applications in brick and mortar retail are thoroughly examined in chapter 2. Chapter 3 is then dedicated to creating a sound theoretical framework for the derivation of hypotheses; two district streams of research, namely technology acceptance and mass media effects are analyzed and major theoretical and empirical findings relevant to the present research are summarized.

Chapter 4 begins with elaborating the procedure taken to build the context specific acceptance model of this dissertation. The remainder of the chapter is dedicated to the model and hypotheses development. Building on the various theories, namely technology acceptance, individual media dependency theory, learning theories, and consumer behavior research, the rational for the inclusion of each building block of the model is thoroughly discussed. Chapter 5 starts by selecting the most appropriate statistical analysis method for testing the research model and associated hypotheses. Following, the research model is operationalized and the procedure of the data collection and the characteristics of the data are discussed. Finally, the PLS-SEM method is used to estimate and analyze the results. In the last chapter (chapter 6) the theoretical implications of the empirical results are thoroughly discussed. Following, using the Importance-performance matrix analysis managerial implications are derived from the results. This chapter closes by an outlook on future research areas. Figure 2 provides a schematic presentation of the structure of this thesis.

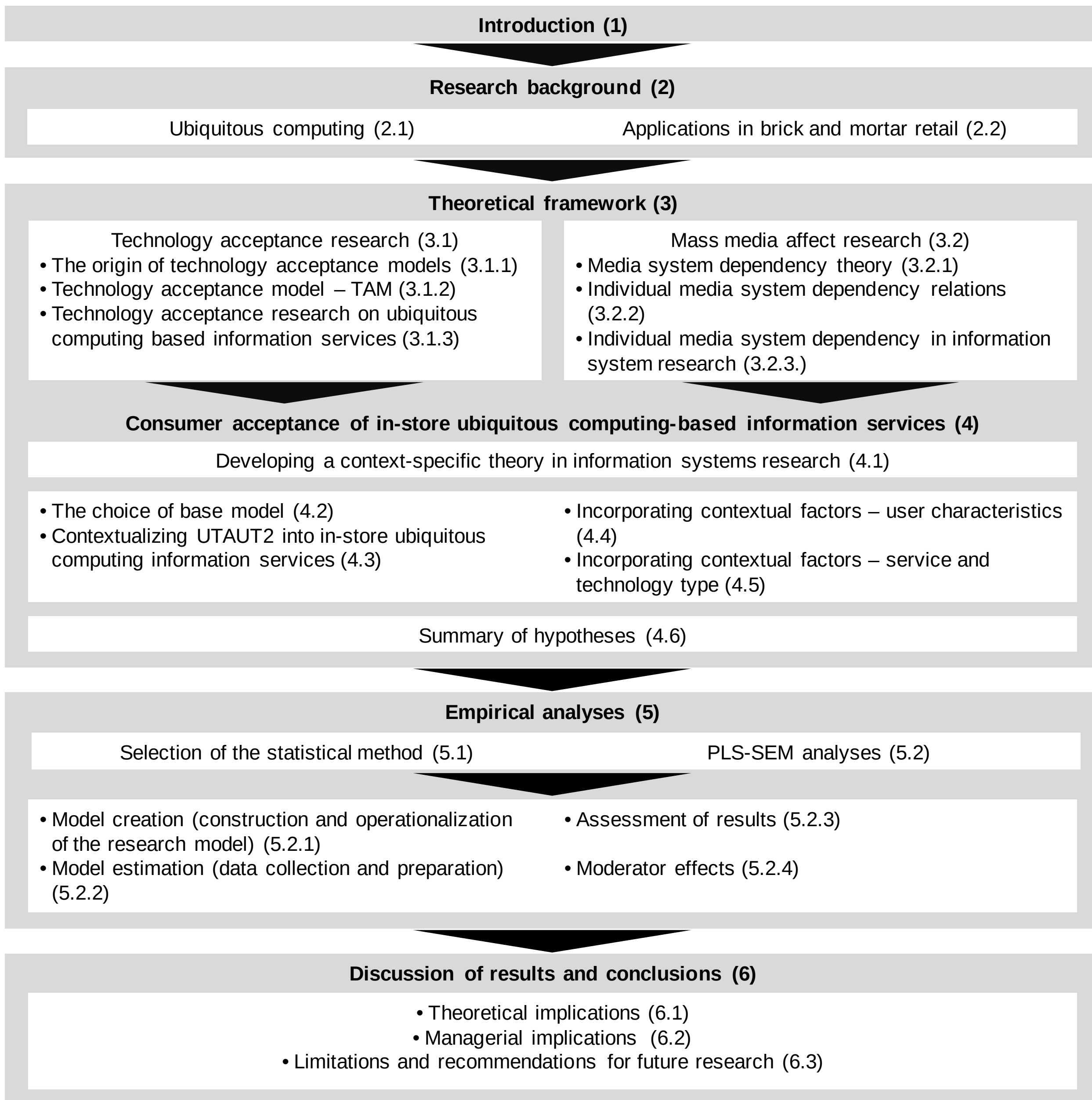


Figure 2: Schematic presentation of the structure of thesis

2 Research Background

When reviewing the literature, depending on the technologies and objectives of the study, various terms are used to address technologies and applications developed to assist the decision making process of customers in brick and mortar retail for example, among others, technology-based innovations for the point of sales (Pantano and Di Pietro, 2012; Pantano and Viassone, 2014), advanced/new technologies in retailing (Pantano, 2010b; Pantano et al., 2013), ubiquitous technologies in retailing (Kourouthanassis and Roussos, 2003; Pantano, 2013; Rothensee, 2010; Roussos and Moussouri, 2004; Struker et al., 2004), pervasive technologies in retailing (Narayanaswami et al., 2011; Pous et al., 2013; Roussos et al., 2002), self-service technologies in retail setting (Dabholkar et al., 2003; Lee et al., 2011). In this dissertation, the notion of ubiquitous computing is selected to address the technologies developed to assist customers while searching and evaluating product information in brick and mortar retail: in-store ubiquitous computing-based information services. The notion of ubiquitous computing is an umbrella concept which can encompass all instances of the current technologies and offer a comprehensive view of their characteristics; therefore, the most suitable for the holistic objectives of this dissertation.

Thus, next, to specify the under scrutiny systems and services of this dissertation the concept of ubiquitous computing, its state of research, and characteristics are examined. Following the state of the academic and industrial research and developments that relate to applications of ubiquitous computing technology in brick and mortar retail are thoroughly investigated.

2.1 Ubiquitous Computing

After the advent and widespread use of mainframes and personal computers, Weiser (1991) adumbrated the third wave of computing labeled as ubiquitous computing. Weiser envisioned a world where boundaries between the physical and digital are blurred and sometimes even completely vanished; a world augmented with intelligent artifacts which provide us with information and services, anytime and anywhere we wish for, in an easy and pleasant way.

For 25 years, intensive multifaceted research area has been emerged around the ubiquitous computing concept (Bell and Dourish, 2007; Caceres and Friday, 2012) pushing the concept gradually from a vision to reality. Although it cannot be claimed that the idea is fully realized many of today's innovations have greatly contributed to the reduction of temporal and spatial limitations of computers, for example technologies as wireless and mobile services, sensor-equipped products and devices, and smart pads and phones among others. This section discusses the evolution and state of the art in the ubiquitous computing research as well as the characteristics of the ubiquitous computing

2.1.1 Evolution of the Research

Weiser delineated his vision of ubiquitous computing in his famous seminal paper, "the computer for the 21st century" (Weiser, 1991) followed by two articles to further elaborate his vision (Weiser, 1993; Weiser and Brown, 1997). Looking from the perspective of technology-human relationship, Weiser and Brown (1997) introduced three eras of computing: the mainframe era, the personal computer era and the ubiquitous computing era.

The first era or the mainframe era was characterized by the one-to-many relationship between computers and human; in this era computers were luxurious and special devices mostly in the hands of experts and used by big organizations or governmental institutions. They were mostly unilateral in their functionality, huge and bulky in their size, and difficult to use in their usability.

The second era was the era of personal computing enabling one-to-one relationship of computer and human. In this era computer has become a sizeable and affordable device with improved functionality and usability so that more people could use their personal device than shared ones.

Having experienced the mainframe and personal computer eras, Weiser considers the evolution of the Internet as the transitional phase of widespread distributed computing which takes us toward a new era. Despite admitting its importance, Weiser doesn't consider the advent of the Internet as a new era but a force behind the rise of a new one; he argues that the Internet by itself doesn't change the human-computer relationship but the consequences of the extensive connectivity facilitated by it. Weiser and Brown (1997) state that "*over the next decade the results of the massive interconnection of personal, business, and government information will* *create a new field, a new medium, against which the next great relationship will emerge"* (p. 2). The third futuristic era of Weiser was entitled as the era of ubiquitous computing in which many computers share each of us, the era of many-to-one relationship.

Categorizing the variations of human-computer relationships into three distinct eras, Weiser tried to emphasize the emerging role of computers in our lives, putting the spotlight on user while talking about the computer technologies. The vision has triggered a new way of thinking among computer scientists which sets the user in the focus while computer vanishes into background. In this regard, Weiser (1991) states that "*the most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it"* (p. 94). As computers become the integrated part of user's activities, users won't be aware of them, in other words users won't perceive them as computers. Weiser (1991) compares this level of integration with "writing" as the first information technology: "*Not only books, magazines and newspapers convey written information, but so do street signs, billboards, shop signs and even graffiti. Candy wrappers are covered in writing. The constant background of "literacy technology" does not require active attention*" (p. 94). In the case of computers, this can be realized in two ways, making them literally invisible for example by miniaturizing the computing devices which could be embedded into the objects or making them invisible in metaphor by integrating them into the user activities for example by offering natural interactions. The vision could be considered the exact opposite point of the virtual reality. Contrary to virtual reality which seeks to bring the physical world into the digital realm the ubiquitous computing is an idea of the pervasive penetration of the virtual world into the physical one; virtual reality simulates the real world, whereas ubiquitous computing enhances it (Weiser, 1991).

Weiser's research group, at the Xerox Palo Alto, has created a laboratory scale realization of the ubiquitous computing vision building two kinds of devices; large-scale stationary devices named live boards which in combination with active badges, one could customize the displayed information and small portable computing devices called tabs (inch-scale) and pads (foot-scale). Based on his research, Weiser (1991) named three technological criteria for realization of the ubiquitous computing vision as "*cheap, low-power computers that include equally convenient displays, software for ubiquitous applications, and a network that ties them all together"* (p. 100).

In terms of service characteristics, the full-blown vision of ubiquitous computing encompasses three main dimensions namely ubiquitous accessibility of information and services, a universal connectivity of information which is a necessary condition of the ubiquitous accessibility, and an unobtrusive and steady level of interactivity. Later, different terms were emerged around the concept of ubiquitous computing through which researchers tried to underline the specific characteristics of their technologies and researches. Pervasive computing, ambient intelligent, and internet of things among others are the most common terms with somewhat different interpretation of the original ubiquitous computing vision, putting the spotlight on one or the other service characteristics of ubiquitous computing (see Table 1).

Seven years after the introduction of Weiser's vision, Lohr and Markhoff (1998) from IBM, for the first time, used the term pervasive computing envisioning the post-pc world where the computers will leave the desktops and will be available everywhere. Later, Hansmann et al. (2003) from IBM, Germany, used the term pervasive computing in line with the vision of ubiquitous computing focusing more on the aspect of the "everywhere at anytime". More focused on the accessibility dimension, they introduced the IBM's definition of pervasive computing as "*convenient access, through a new class of appliances, to relevant information with the ability to easily take action on it when and where you need to*" (Hansmann et al., 2003, p. 11).

Simultaneously to IBM's pervasive computing vision, Philips' executive vice president, Pieper (1998), introduced the term ambient intelligence in a series of presentations. The presentations were targeted to the Philips' own employees and brought about the vision of digital living room equipped with various sensors which could intelligently response to speech or gesture of the people. "*Ambient intelligence refers to electronic environments that are sensitive and responsive to the presence of people"*(Aarts and Encarnacao, 2006); building on the vision of ubiquitous computing, the focus of the term is more on the interactive aspect of ubiquitous computing.

More focused on the automated things to things connection and interaction, the term internet of things has been used in 1999, for the first time by Kevin Ashton, co-founder of AutoID Labs, a world-wide network of academic research laboratories in the field of networked RFID and emerging sensing technologies (Caceres and Friday, 2012). However at its inception, the vision was mostly focused on the RFID and barcode enabled items in the supply chain enabling an improved item visibility for a greater business efficiency and accountability (Caceres and Friday, 2012); soon it has been picked up by the ubiquitous computing researchers for the similarity of the concept and its potential applications in line with the realization of ubiquitous computing vision. The paradigm of internet of things "*continues on the path set by the concept of smart environments and paves the way to the deployment of numerous applications with a significant impact on many fields of future every-day life*" (Giusto et al., 2010, p. v). Table 1 summarizes the above mentioned terms around the vision of ubiquitous computing along with their most common definitions. In addition, the highlighted dimensions of ubiquitous computing addressed by each definition are listed.

Table 1: Different terms around the concept of ubiquitous computing and their highlighted aspects

Term	Highlighted dimension/s	Definitions
Ubiquitous computing	Connectivity Accessibility Interactivity	*Machines that fit the human environment, instead of forcing humans to enter theirs* (Weiser, 1991, p. 104). *Computers embedded in our natural movements and interactions with our environment, both physical and social* (Lyytinen and Yoo, 2002, p. 63). *A highly embedded technology that obtains and processes information from the environment. It can adapt to various situations and configure its services autonomously in order to assist and enhance interactions between humans and the real world. To this end ubiquitous computing even uses implicit input to reduce the level of interventions. Summarizing, ubiquitous computing is the cooperation of IT-artifacts in the environment to support the user with customized services on demand, while the interaction of the user with IT-artifact* (Hoffmann et al., 2011, p. 5). *Countless very small, wirelessly intercommunicating microprocessors, which can be more or less invisibly embedded into objects. Equipped with sensors, these computers can record the environment of the object in which they are embedded and provide it with information processing and communication capabilities* (Friedewald and Raabe, 2011, p. 55).
Pervasive computing	Accessibility	convenient access, through a new class of appliances, to relevant information with the ability to easily take action on it when and where you need to (Hansmann et al., 2003, p. 11). *Interconnected technological artifacts diffused in their surrounding environment, which work together to sense, process, store and communicate information to ubiquitously and unobtrusively support their users' objectives and tasks in a context-aware manner*.(Kourouthanasis and Giaglis, 2008, p. 14) *Ubiquitous connected computing devices in the environment which are very tiny, even invisible, either mobile or embedded in almost any type of object* (Singh, 2010, p. 1).

Ambient intelligence	Interactivity Proactively	*Ambient intelligence deals with a new world of ubiquitous computing devices, where physical environments interact intelligently and unobtrusively with people. These environments should be aware of people's needs, customizing requirements and forecasting behaviors* (Ramos et al., 2008, in the abstract)
Internet of things	Connectivity Object-to-object interaction (communicating things)	*The pervasive presence around us of a variety of "things" and "objects", such as RFID, sensors, actuators, mobile phones, which, through unique addressing schemes, are able to interact with each other and cooperate with their neighboring "smart" components to reach common goals* (Giusto et al., 2010, p. v).

As any other technology-based vision, the most basic building block of the realization of the vision of ubiquitous computing is the technological feasibility. From the technological point of view, ubiquitous technology is not a single independent technology or a discrete field of technology (Sen, 2012) but it encompasses a wide range of technological areas and devices (Bell and Dourish, 2007; Friedewald and Raabe, 2011; Saha and Mukherjee, 2003).

Since the introduction of the ubiquitous computing vision the technological landscape has changed thoroughly. Today, indeed computer devices have left the desktops. In industrialized countries, the Internet as a powerful and overarching network has become part of the vital infrastructures. The commercial versions of Internet-enabled taps and pads in the form of smart phones and tablets are now available for more than 10 years. Considerable advances in hardware developments, localization systems and mobile communication technologies all have advanced the ubiquitous computing vision toward the technological feasibility. In general, enabling technologies of ubiquitous computing can be divided into three broad areas namely devices, networking, and middleware (Saha and Mukherjee, 2003). Table 2 presents a list of enabling technologies for ubiquitous computing which their advances in recent years have particularly been the core driving force of its realization (Friedewald and Raabe, 2011).

Table 2: Enabling technologies for the vision of ubiquitous computing

Enabling technologies	Their share in realization of the vision of ubiquitous computing
Devices	
Atomic light, temperature, motion, and voice sensor network	Atomic components which link the real world with the digital world (Atzori et al., 2010). They could automatically capture the context information and trigger an intelligent action by sending the information

	to the other devices in the network; enabling context awareness and autonomy (Sen, 2012).
Localization systems as global positioning system (GPS) based sensors	Automatically capture spatial information of the user and/or device and trigger an intelligent action by sending the information to the other devices in the network.
Radio frequency identification (RFID)	Automatically revealing the identity of the given object, RFID is one of the most common underlying technology for the current ubiquitous computing solutions (Friedewald and Raabe, 2011). Integrated into a network, enables the association of unlimited amount of information to the objects and/or persons.
Micro-electronics (enabled by semi-conducting polymers)	Embedding the computing elements in objects (Alcañiz and Rey, 2005; Chalasani and Conrad, 2008)
Networking	
Mobile communication technologies such as universal mobile telecommunications systems (UMTS), near field communication (NFC), ultra-wide band technology (UWB)	Data exchange between communication infrastructure, end devices, and terminal devices (Lagasse and Moerman, 2006).
Middleware	
Interactive user interfaces	Precise knowledge of context enabling personalized responses (Wasinger and Wahlster, 2006)e.g. enabling physical interaction and/or external and internal automatic context sensing e.g. sensing the location (external) and emotional states or intended actions(internal) (Friedewald and Raabe, 2011)

In an article titled "20 years past Weiser: what's next?", Ferscha (2012) traces the evolutionary path of the past research around ubiquitous computing in an attempt to outline the future research directions. Considering three components of ubiquitous systems namely hardware (devices and networking), middleware (interactive user interfaces) and applications (services), he identifies three generations of research themes namely connectedness, awareness, and smartness.

The first generation of the research starting from late 90s to early 2000s was mostly a response to "some computer science issues in ubiquitous computing" which Weiser (1993) himself published in a paper under the same title. The paper discusses the most fundamental technologies of its time to leverage the first applications of ubiquitous computing; here, the issue of connectivity plays a central role. The research in this phase picked up the pace by the advances in networking technologies as the gate packing, new wireless communication standards and most importantly the rapidly growing Internet (Ferscha, 2012). Network technology advances added to the technological progress in electronics miniaturization led to the emergence of the first networks of ubiquitous systems characterized by special-purpose computing and information appliances.

Parallel to the hardware developments, in the software research, new user interfaces were developed to bridge the gap between digital and physical space. In this time, the user interface research mostly focused on developments of natural interfaces to support common forms of human expressions (Abowd and Mynatt, 2000). An example of this kind of interfaces is tangible user interface which is seeking to integrate the digital information and objects in a way that the manipulation of physical objects leads to the changes in the targeted digital information (Ishii and Ullmer, 1997). Applications in this time mostly focused on localization of people and objects for location services, shared meeting tools for office uses and invisible collaborative information filtering (Weiser, 1993).

Building on networking technologies and connectedness, the second generation of ubiquitous computing research emerged spanning the early to mid-2000s. The focus in this phase shifted towards the concept of awareness as context and situation awareness, self-awareness, and future and resource awareness (Ferscha, 2012).

Sensor based recognition systems, knowledge representation and processing technologies enabled objects to capture data through various sensors and interpret them so that they became aware of their context (Ferscha, 2012). The concepts of context and context-aware system were redefined for the novel research realm of ubiquitous computing; context was defined as "*any information that can be used to characterize the situation of an entity. An entity is a person, place or object that is considered relevant to the interaction between the user and applications themselves*" (Dey, 2001, p. 5) and context-aware system as "*a system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task*" (Dey, 2001, p. 5). New spectrum of context-aware systems has been developed exceeding the then existing location systems (Hightower and Borriello, 2001; Schmidt et al., 1999).

Transferring the advances in context awareness to the user interface design generated a new paradigm of human-computer interaction namely implicit interaction. Implicit human-computer interaction is defined as "*an action performed by the user that is not primarily aimed to interact* *with a computerized system but which such a system understands as input*" (Schmidt, 2000, p. 192). In other words, such a system is capable of capturing the user's interaction with the environment to evaluate the situation (Schmidt, 2002). Consequently, the system is able to synthesis the explicit input from the user with the automatically captured context-based information (implicit input) to offer a context-specific service to the user's request. Such interfaces are very important for the realization of the notion of ubiquitous computing as they reduce the interference of the computing system in user activities (Abowd and Mynatt, 2000) and consequently push the computer device into the background.

Furthermore, in this time, a new understanding of the concept of invisibility in ubiquitous computing has been introduced; Satyanarayanan (2001) called the Weiser's vision of complete invisibility an ideal and far from practice. He then offered an allegedly practical interpretation of invisibility as "*minimal user distraction*" arguing that "*if a pervasive computing environment continuously meets user expectations and rarely presents him with surprises; it allows him to interact almost at a subconscious level*" (p.2)

From the application point of view, the advances on wireless technologies and protocols as well as sensor technologies offered a huge potential on automatic and remote monitoring, analysis, and execution, promising for various application areas for example industrial applications (machine monitoring, pervasive maintenance), health applications (patient monitoring), and home applications (water monitoring, temperature and light monitoring) (Akyildiz and Vuran, 2010; Lewis, 2004) among others.

The third wave of ubiquitous computing research has been started in the mid-2000s. Having the foundation of connectedness and awareness, in third generation of the ubiquitous computing research, the attention has turned towards the semantics of systems, services, and interactions to lift the situations and actions into a novel level of sense (Ferscha, 2012), that is smartness. Here research has focused on highly complex cooperative and coordinated ensemble of digital artifacts capable of autonomous and spontaneous configuration toward a complex system (Ferscha, 2012). Supplementing the context and situation awareness with semantics enables a system to take smart decision and evolve itself by adapting to the environment. Such systems "*are able to respond in a rational way in many different situations choosing the actions with the best* *expected result, so making environment not just more connected and efficient, but smarter*" (Amato et al., 2012, p. 412). Ferscha (2012) postulates that the connection of a huge number of diverse ensembles of digital artifacts embrace the future generation of ubiquitous computing. Taking the current level of technology penetration into the fabric of our everyday life as evidence with billions of personal computer nodes and Internet-enabled smart phones, Ferscha (2012) argues that we have already arrived to the point of large-scale, complex, technology-rich societal setting.

Tracing the trajectory of past research around the ubiquitous computing vision, it becomes evident that the previous research mostly was focused on technological developments as well as the feasibility of potential applications and services. To make the future research agenda book, Ferscha (2012) created a web contribution portal to collect the future research challenges. The portal could collect 100 research challenges from the invited experts in the field. Nine chapters have been evolved from the collected challenges for the research agenda book (see Figure 3). Among them, chapter seven is especially relevant for the motivation of this dissertation as it is dedicated to human-centric adoption. In their paper, reviewing progress, opportunities, and challenges of ubiquitous computing, Caceres and Friday (2012) address this issue emphasizing that the main challenges of the implementation of ubiquitous computing applications today are economic rather than technical; to foster the way of research and development projects into the market, the future research should focus on the user and who and why of using ubiquitous computing-based applications and services. To bring the vision of ubiquitous computing closer to realization, in addition to technological research, substantial investigation into the human behavior is needed (Aarts and Encarnacao, 2006). Figure 3 summarizes the evolution of research around ubiquitous computing as well as future research challenges.

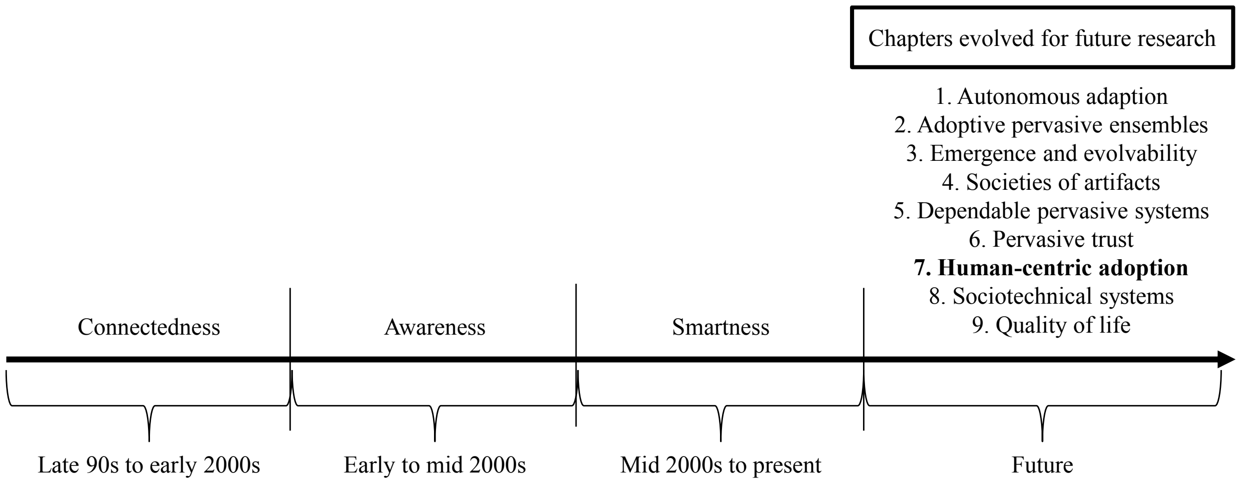


Figure 3: Chronological evolution of research around ubiquitous computing and future research challenges based on the work of Ferscha (2012)

2.1.2 Characteristics

As mentioned in the previous section, new streams of research in various disciplines, as hardware and networking, software, middleware, and system architecture, various application areas, and human-computer interaction, have emerged around the vision of ubiquitous computing. The broad and organic evolution of the research around the vision led to the advent of different perspectives concerning the features and characteristics of ubiquitous computing (Bell and Dourish, 2007; Hoffmann et al., 2011). Therefore, the characteristics of ubiquitous computing cannot be described in universal terms since so much depends on the context of its applications. Different applications demand different technological sources and features. For example, a simple RFID-enabled passport is as an application instance of ubiquitous computing; at the same time, a smart home environment is also an application case of ubiquitous computing. Both applications encompass some features making them eligible to be labeled as the ubiquitous computing application, though to different degrees. It is evident that the characteristics of RFID enabled passport, enabling the airport authorities to automatically check the personal information and authenticity of travel documents, cannot be identical to the characteristics of a fully digitalized home environment which automatically captures its residents living behavior, desired temperature and light level and gradually learns all anomalies to autonomously adopt home systems to the expectations of its residents. To sum up, in reality there is no clear-cut boundary between a ubiquitous system and a non-ubiquitous one; rather there exists a degree to which a system encompasses a set of characteristics of ubiquitous computing or none.

Based on the Weiser's description of the concept, in terms of service characteristics, an ideal instance of ubiquitous computing encompasses ubiquitous accessibility, universal connectivity, and unobtrusive interactivity. However, each of these characteristics can move along opposite ends of a continuum. Accessibility of information and services moves along a continuum with the "traditional desktop" and "everywhere at any time" standing on its opposite ends. Interactivity moves along a continuum with two ends of "desktop bound" and "constant companion", and connectivity moves along a "sole device and information" and "every object and user" continuum.

To put all these dimensions in a single platform, a three-dimensional-continuum concept of ubiquitous computing service characteristics is introduced in Figure 4; these dimensions jointly measure the ubiquitous computing capabilities of a technology application, however as mentioned above, a ubiquitous computing application might encompass features from only one or two dimensions.

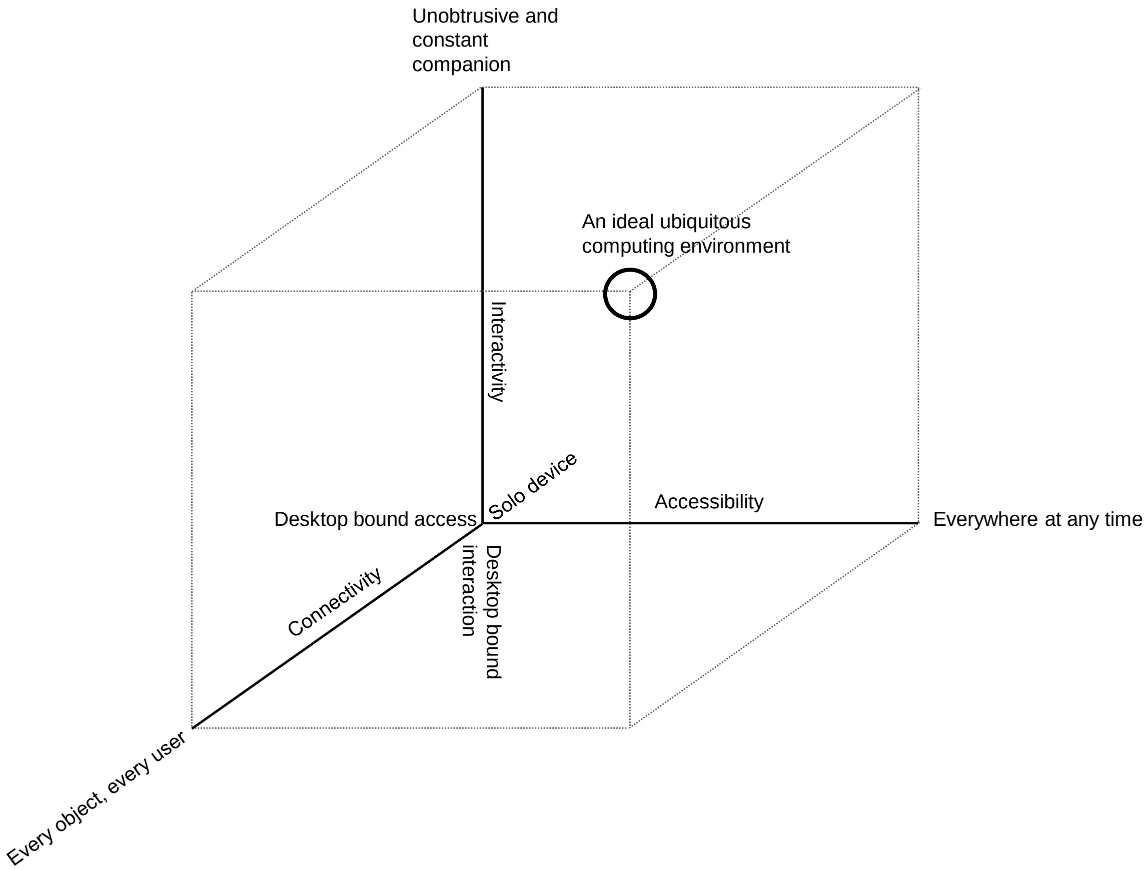


Figure 4: Characteristic dimensions of ubiquitous computing applications

When reviewing the literature, various bundles of system characteristics are mentioned for ubiquitous computing service dimensions. Table 3 summarizes the characteristics mentioned by different researchers to specify a ubiquitous computing system. Therefore, the remainder of this section is dedicated to a brief description of each these three dimensions in terms of various ubiquitous computing system characteristics.

Table 3: Characteristics of ubiquitous computing systems

		Accessibility				Interactivity						
									Embedded-ness			
Source	Connectivity	System availability	Device mobility	User mobility	Application mobility	Context awareness	Implicit interaction	Adoption/ Autonomy	Physical	Cognitive	Natural interaction	Simplicity
(Aarts and Encarnacao, 2006)	✓	-	-	✓	-	✓	-	✓	✓	-	✓	✓
(Abowd, 1999)	✓	-	-	-	-	✓	-	✓	✓	-	-	
(Abowd and Mynatt, 2000)	✓	✓	-	-	-	✓	✓	-	✓	-	✓	✓
(Banavar and Bernstein, 2002)	✓	-	✓	-	✓	✓	-	✓	✓	-	-	-
(Bell and Dourish, 2007)	✓	-	✓	-	-	-	-	-	✓	✓	-	-
(Friedewald and Raabe, 2011)	✓	✓	✓	-	-	✓	-	✓	✓	-	-	-
(Gabriel et al., 2006)	✓	✓	-	-	✓	✓	-	✓	✓	-	-	-
(Kim et al., 2009)	✓	✓	✓	-	-	✓	-	✓	✓	-	-	-
(Kourouthanassis et al., 2008)	✓	✓	-	✓	✓	✓	✓	✓	✓	✓	✓	-
(Kurkovsky, 2005)	✓	-	✓	-	-	✓	-	✓	✓	-	✓	-
(Satyanarayanan, 2001)	✓	-	✓	-	-	✓	-	✓	✓	✓	-	-
(Schmidt, 2002)	-	-	✓	-	-	✓	✓	-	✓	-	-	-
(Sen, 2012)	✓	-	✓	-	-	✓	-	✓	✓	-	-	
(Spínola and Travassos, 2012)	-	-	✓	✓	✓	✓	-	✓	✓	-	-	-

Connectivity

The connectedness is a primary milestone towards achieving the ubiquitous computing vision (Figure 3). The connectivity is in fact the most mentioned characteristic of ubiquitous computing in the literature thus illuminating its importance (see Table 3). It is the necessary but not sufficient condition for the accessibility and interactivity. That is the higher the level of the connectivity between devices and information the more accessible and interactive applications can be designed. Communication technologies, in particular wireless technologies enable a seamless interaction and information access without a tangible connection step (Want et al., 2002). It is the importance of the connectivity aspect which Weiser and Brown (1997) consider the evolution of communication technologies, specifically the Internet as the transitional phase of the widespread distributed computing which takes us toward a new era of ubiquitous computing.

Accessibility

The central idea of ubiquitous computing also apparent in its name is the ubiquity and pervasiveness of its applications and services. Here, the goal is to go beyond the spatial and/or temporal boundaries of the traditional computing and ideally make computing applications accessible anywhere at anytime. As a consequence, a user is not required to go to a certain place to access a given computing service but the service would be accessible independent from the user's location. Accessibility in this context refers to the ability of a system to allow its users a permanent access to information sources regardless of their location, albeit within the borders of the system. The level of the accessibility accordingly is the degree to which a system can fulfill the unbroken access. The omnipresence of ubiquitous applications can be realized by either the physical mobility (user and device mobility) or the logical mobility (application mobility) (see Table 3).

The user mobility refers to the capability of a system to provide the user with services while she moves within the system boundaries. Referred to as the local mobility, the first applications of its kind was discussed in the organizational setting enabling employees to use computing services while moving from office to office within a vicinity (Luff and Heath, 1998; Perry et al., 2001). The current technological development in small-size sensors and microelectronics enables the integration of computing elements in everyday objects (Alcañiz and Rey, 2005; Chalasani and Conrad, 2008) leading to the rise of smart environments. While a user moves in such smart environments, she can use the computing services. The device mobility, on the other side, enables users accompanied by a mobile device to access computing services while moving from one location to another (Banavar and Bernstein, 2002). Indeed the mobile technology is addressed as the key enabling technology in ubiquitous computing (Friedewald and Raabe, 2011). Furthermore, making applications and information move between different devices while tracking the user, referred to as the application mobility (Yu et al., 2013). The application mobility is another way to offer a pervasive access to information sources (Banavar and Bernstein, 2002). da Costa et al. (2008) refer to it as the logical mobility contrasting to the physical (user and device) mobility. For example the cloud computing technology is one of the technologies enabling its users to access their information content in other devices regardless of where they have stored and worked on in the first place (Yu et al., 2013). Caceres and Friday (2012) reviewing the progress, opportunities and challenges of ubiquitous computing in its 20th anniversary, spot the cloud computing progress as an opportunity to leverage the ubiquitous computing infrastructure.

While the notion of the mobility mostly encompasses the spatial aspect (everywhere) of the accessibility, the accessibility of a system beyond the temporal boundaries (anytime), often referred to as the system availability, is another important feature of ubiquitous computing applications.

Interactivity

An important component of Weiser's (1991) vision is making computing "*an integral, invisible part of people's lives*" (p. 94). Invisibility in this context refers to an ideal level integration of a system into the user's environment or activity resulting in an absolute attention-free interaction of the user and the system. In other words, while interacting with a technology device to perform a task, the user can fully concentrate on his primary activities and goals.

Human attention resources are limited; we are not capable of collecting and processing all existing inputs in our surrounding environment. To function, the human attention filters out the surrounding information, selecting some and ignoring others (Sanders, 1998). Thus, by considering the everywhere anytime accessibility of computing artifacts, a new problem arises; Garlan et al. (2002) address this problem by emphasizing that while computing systems increasingly become accessible, the bottleneck in computing shifts from technological aspects to the limited resource of human attention. In the case of ubiquitous computing, envisioning integration of the computing in everyday life, the issue of the attention becomes even more important, as users are supposed to interact with a computing artifact while they are preoccupied with some other real-world interactions as walking, talking, shopping or driving (Garlan et al., 2002; Scholtz and Consolvo, 2004). Therefore, the everywhere anytime accessibility dimension of ubiquitous computing should be complemented by an unobtrusive level of interaction to realize the notion of ubiquitous computing. In this context, interactivity refers to the ability of a system to offer an unobtrusive interaction, demanding no attention from the user. The level of the interactivity accordingly is the extent to which a system is capable of a distraction-free interaction with its users.

As shown in Table 3, regarding the interactivity dimension of ubiquitous computing, six characteristics are mentioned in the literature, each of which, alone or in combination with others, contribute to the realization of a degree of distraction-free interaction of the user and the computing artifact.

The context awareness is a feature mentioned by many authors as an enabler for a higher level of interactivity. A context aware ubiquitous artifact can capture the contextual information from the surroundings (Abowd, 1999) and accordingly personalize its services to the needs of its user (Aarts and Encarnacao, 2006; Abowd, 1999; Dey, 2001). Related to the feature of the context awareness is the notion of the implicit interaction. The implicit interaction is the ability of a system interface to monitor the user's interaction with the environment even when she is not directly interacting with the system (Schmidt, 2000). Consequently, the system is able to synthesize the explicit input from the user with the automatically captured context-based information (implicit input) to offer a context-specific service to the user's request. Such interfaces reduce the interference of the computing system in user activities (Abowd and Mynatt, 2000). For example, consider a mobile product recommender system for an in-store shopping situation which can automatically capture the users' positions (context data); by analyzing the position data, the system can implicitly capture the user's preferences (implicit input) and consider them while making product recommendations (Fang et al., 2012). Features of the adoption and autonomy are the consequences of further development of context aware systems. Enhancing the context awareness with semantics enables a system to take a smart decision and evolve itself by adapting to the environment (Amato et al., 2012), and when needed even act on behalf of the user (Aarts and Encarnacao, 2006). All these features aim to free the user from constant instructing a system to support her given task (Rekimoto and Nagao, 1995) and consequently offer a high level of interactivity.

Another important feature related to the interactivity dimension is the embeddedness. The notion of the invisibility in the Weiser's ubiquitous computing vision can be literally realized through embedding the computing devices into the physical world. Often prerequisite for the context awareness, embedding computing artifacts in the user's environment, device, and clothing and even in her body leads to disappearance of the computing technology from the user's sight and thus consciousness, hence demanding no attention from the user.

However, as mentioned in the previous section, the invisibility is not just a matter of the embedment of computing artifacts in the environment; it is also about how the user perceives the computer; referred to as the cognitive embeddedness and invisibility, this feature is based on the idea that if a user accepts a computing artifact as a natural part of her life, it disappears from her consciousness. Conceptually overlapping with the feature of the cognitive invisibility are features of the natural interaction and simplicity. The concept of the simplicity or ease of use is nothing new in the field of human-computer interaction; designing information artifacts in a way that they perfectly fit to the user requirements and underlying task makes them part of the task (Norman, 1999). Natural interaction interfaces as well as the implicit input contribute to the general simplicity of a system (Hoffmann et al., 2011).

The simpler the use of a technology, the faster it passes the surface of awareness; so novel technologies such as ubiquitous computing technologies "*should contribute to the development of easy to use and simple to experience products*" (Aarts and Encarnacao, 2006, p. 1).

2.2 Applications in Brick and Mortar Retail

In the business context, the potential of ubiquitous computing in value creation for example by the process and product improvement as well as new service development (Fleisch and Tellkamp, 2006; Gershman and Fano, 2006) has triggered the rise of plethora of applications. A discussion of all possible application areas is beyond the scope of this work, interested readers can find reviews of these applications in the literature (e.g. Friedewald and Raabe, 2011; Gabriel et al., 2006). This section offers an overview of the research in academia as well as industry on applications which, based on the characteristics of ubiquitous computing discussed in the previous section, can be classified as instances of ubiquitous computing technologies in brick and mortar retail.

Internet-induced changes in the customer behavior along with recent technology advances to enhance retailing operational processes and customers' shopping activities and the increasing willingness of customers to use new technology based services drive the retailing sector to be more innovative for the sake of sustaining and growing profitability (Y.-T. H. Chiu et al., 2010; Pantano and Viassone, 2013).

Initially, retailers focused on harnessing the advantages of ubiquitous computing in terms of support-related technologies (Hristov et al., 2015), for example in logistics and supply chain practices. Less visible for customers (Hristov et al., 2015), these technologies can boost the efficiency of retail offer delivery by enabling a greater control over the purchase orders, inventory, and product related information (Bennett and Savani, 2011; Garrido Azevedo and Carvalho, 2012; López et al., 2011).

However, in recent years, there has been a growing interest on ubiquitous computing-based customer-related innovations; such innovations are visible for customers and their key impact on the brand positioning, growth and differentiation have already been proven (Hristov et al., 2015). As a consequence, during the last decade, a growing body of research has been raised around the development of customer oriented in-store ubiquitous computing systems (Bodhani, 2012; Pantano and Di Pietro, 2012; Pantano and Viassone, 2013).

By deployment of ubiquitous technologies in retail, various innovative in-store applications came into being, enabling retailers to offer their customers personalized services in an accurate and prompt manner (Kourouthanassis and Giaglis, 2005); applications and services which make it possible for retailers to transfer the advantages of the online world to the physical world (Pous et al., 2013). Imagine a scenario where a customer enters a store to buy a pair of trousers. Here the customer's options to gather information are limited to the product labels and salespersons assistance. None of these choices are similar to what the customer experiences in the online world with regard to the obtaining customized, interactive, and automatic information, recommendations, and comparison options.

Ubiquitous computing-based in-store applications make it possible to offer the customer an automatic and personalized shopping assistance, tailored to her preferences e.g. support the store navigation and show the way through the store, advise and give recommendation for a certain product and/or relevant ones (cross-selling), compare the products in the store, spot the special offers, and give additional information about the products. Technologies such as information kiosks (Zielke et al., 2011), interactive displays, mobile shopping assistances (Resatsch et al., 2008; van der Heijden, 2006), and smart mirrors offer customers all in-store and sometimes complementary information in a similar way as the Internet does. To sum up, such technologies can "*influence the course of searching for, choosing, and comparing products, as well as interacting with products and providing marketers new tools to understand consumer preferences and needs*" (Pantano and Naccarato, 2010, p. 202), comparable to the online world (see Table 4).

Before the advent and widespread adoption of smart mobile devices, the realization of ubiquitous computing services in brick and mortar retail could be only approached in two ways, *"to provide the user with mobile devices"* (device mobility) or *"to distribute different devices in the environment"* (user mobility) (Alcañiz and Rey, 2005, p. 7). However, recently Pantano and Viassone (2014), considering the prevalent use of smartphones, categorize in-store ubiquitous computing technologies into three main groups namely, touch screen displays/ store-owned totems, hybrid systems consisting of store-owned portable devices, and systems for consumers' own mobile devices.

As the core topic of current dissertation revolves around the user acceptance, the device ownership is an important aspect to consider while categorizing the in-store technologies. Technology device ownership is believed to increase the acceptance likelihood of new applications based on the already owned device (Niehaves et al., 2012; Tretiakov and Kinshuk, 2005). In general, users feel more confident using their own devices while being engaged in a new context as obtained experience and skills from the previous usage can be easily utilized in the new context (Prete et al., 2011). Considering this aspect is especially important for retailers as the level of investment on store-based systems is significantly higher than mobile applications. Therefore, in this dissertation the current in-store systems are classified in two distinct categories namely store-based systems (store owned devices) and software applications offered on the customers own potable smart devices.

Systems included in the first category are technologies which are owned by and are part of the store (Melià-Seguí et al., 2013; Pantano, 2010b; Pantano and Naccarato, 2010); current examples are multimedia information desks, interactive displays, smart fitting rooms, smart mirrors and smart trolleys.

The second category includes applications for consumers' own mobile devices (Gao et al., 2010; Kowatsch et al., 2011; Kowatsch and Maass, 2010). The recent technological advancement in mobile phone and networking technologies along with the exponential growth of the number of mobile phone users has opened a new avenues to the value creation for retailers (Yang, 2010). In fact mobile computing is a subset of ubiquitous computing (Saha and Mukherjee, 2003). Yang (2010) addresses the potential of mobile-based services in the store as "*personal shopping assistance for customers on move*" (p. 262) which can revolutionize customer experiences in traditional brick and mortar stores by

- ✓ *creating a real-time interaction between a retailer and a consumer;*
- ✓ *assisting a consumer in making smart purchasing decisions by providing customized product/service information; and*
- ✓ *delivering non-intrusive mobile marketing to consumer that is based on consumer preferences and priorities.*

Applications such as localization apps and product information search and recommendation apps tend to use consumers' personal mobile devices as the main interface; for example, Välkkynen et al. (2011) introduce a mobile application called mobile augmented reality for presenting product information to the customers. The system allows customers to see the three-dimensional model of product contents as well as additional product related information on their mobile phones without opening of the package. Similar applications named as Shelf Torchlight (Löchtefeld et al., 2010) and mobile product magnifier are introduced by Innovation Retail Laboratory, an application-related research lab, a cooperation project of the German Research Center for Artificial Intelligence (DFKI), the retailer GLOBUS, and Saarland University.

Table 4 lists the main service features of ubiquitous computing-based in-store applications (both store-based and mobile-based) along with the web-based retailing service characteristics in order to highlight the similarity of the offered services.

Table 4: Comparison among ubiquitous computing-based in-store systems and web-based retail adapted from (Pantano, 2013)

	Ubiquitous computing-based store systems	Ubiquitous computing-based mobile systems	Web based retailing
Facilities	Fast response System flexibility Entertainment System available in the point of sale Context awareness Reactive to consumers' interaction Consumers' usage choice	Fast response System flexibility Entertainment System based on consumer's own smart phone Context awareness Consumers' usage choice	Fast response System flexibility Entertainment System available online Context awareness Compulsory the use of a computer
Product information search assistance	Product variety Detailed and customized product information Product comparison among available items	Product variety Detailed and customized product information Product comparison among available items	Product variety Detailed and customized product information Product comparison among products available through the network
Product selection assistance	Virtual assistance Real salesperson assistance (physical support) Several payment modalities	Assistance through network (also online assistance possible through network connection) Real salesperson assistance (physical support) Several payment modalities	Online assistance (through network connection) No real salesperson assistance Limited payment modalities
Space	Fixed Navigational efficiency Possible location indicator	Open navigational efficiency Location indicator	Virtual navigational efficiency No locator indicator
Time	Opening hours	Opening hours	Always open
Further improvements	Retailers investment in both hardware and software	Retailers investments mainly in software	Retailers investments mainly in software

Recent technological advances have enabled the deployment of various pilot projects (Kourouthanassis and Giaglis, 2005). Although, either in the prototype phase or in a limited number of stores various ubiquitous computing-based retail applications can be found on the market.

Table 5 and Table 6 list the current in-store systems (respectively store-based and based on customers mobile devices) as well as their supporting technologies, functionalities and the corresponding industry or research institution. Initiated both by the academia and industry, recent approaches are increasingly focused on providing customers with customized information services (Hilton et al., 2013; Marshall et al., 2012; Wang, 2012).

Table 5: An overview of existing store-based systems, source: (Al-Kassab et al., 2010; Anon, 2014, 2012a, 2012b, 2002; Konomi and Roussos, 2006; Kourouthanassis and Giaglis, 2005; Swedberg, 2007; Tellkamp and Quiede, 2005)

Application	Service	Pilotproject/product by	Enabling technology/ies
Smart Mirror	✓ Product information ✓ Product recommendation	✓ Galeria Kaufhof (METRO group) & Gerry Weber ✓ Burberry London: Flagship Store ✓ Mi-Tu Hongkong ✓ Levi Strauss & Co.	RFID
Smart fitting room	✓ Product information ✓ Product recommendation ✓ Assistance requesting additional items	✓ Galeria Kaufhof (METRO group) & Gerry Weber ✓ Mi-Tu Hongkong ✓ Prada ✓ Valdac global brands – memove	RFID (+LCD-Monitor, Touch Screen)
Multimedia information kiosk	✓ Product information	✓ Future Store Metro ✓ Mitsukoshi, Ltd	Barcode Scanner RFID
Personal Shopping Assistant (PSA)	✓ Product information ✓ Assistance ✓ In-store navigation ✓ Transmitting data to cashier	✓ Future Store Metro ✓ MyGrocer project	Barcode scanner, RFID enabled loyalty card

Smart checkout	✓ Self-checkout ✓ Faster checkout ✓ Checkout with PDA (sales persons have PDAs with customer purchase history)	✓ Valdac global brands – memove ✓ I.T.S. international ✓ Burberry London ✓ Future Store Metro	RFID
Smart shelves	✓ Product information	✓ Mitsukoshi, Ltd ✓ Galeria Kaufhof (METRO group) in collaboration with Gerry Weber	RFID
Loyalty card	✓ Payback loyalty card ✓ Saves purchasing history, alert to sales desk	✓ Future Store Metro ✓ Mi-Tu	RFID

Table 6: An overview of mobile applications,, source: online research among others on iTunes, Google Play, and individual websites

Application	Services	Pilot project/product by	Enabling technologies
Mobile Apps	✓ Store Finder ✓ Store Map ✓ Special/insider-only offers and deals ✓ Product information ✓ Inventory and price check ✓ Product recommendation ✓ Event calendar ✓ Connection to social networks ✓ Gift registry ✓ Paying via customer account	✓ Macy‘s ✓ Walmart ✓ American Apparel ✓ Benetton ✓ Tchibo ✓ Gap Inc Stores: GAP, Banana Republic, Piperlime, Old Navy, Athleta ✓ H&M ✓ Sport Scheck ✓ Douglas ✓ Metro and Pickbe ✓ Neiman Marcus	Barcode Scanner QR Code Scanner RFID Mobile Internet GPS Beacons

3 Theoretical Framework

One of the fundamental objectives of the current dissertation is the development of a theoretically found model enabling to understand, explain, and predict the individuals' behavior regarding the acceptance and use of in-store ubiquitous computing-based information services. The first step in building a theoretically found model is drawing a theoretical framework, a system of theory/theories along with their assumptions and expectation which functions as a lens with which a researcher observes the research questions. Eisenhart (1991) defines the theoretical framework as "*a structure that guides research by relying on a formal theory; that is, the framework is constructed by using an established, coherent explanation of certain phenomena and relationships*" (P. 205). In line with constructing the theoretical framework of this dissertation, the current chapter is dedicated to introduction and discussion of the theoretical basis required to explain the acceptance of in-store ubiquitous computing-based information systems.

The theoretical framework of this research incorporates two different set of theories. For clarity, in this chapter, these theories are treated independently. First, regarding the technology acceptance research, relevant concepts and models are discussed. In order to do so, different approaches in the information system acceptance research are reviewed and the approach taken by this dissertation is highlighted. Following, considering the research objectives of this dissertation, the most relevant technology acceptance models as well as corresponding empirical research in the field are synthesized.

Next, as one of the objectives of this dissertation is to explore the influences of the expanding trend of individuals' Internet-based information use on the user acceptance of in-store ubiquitous computing-based information services, the second theory, namely media system dependency theory which is used to explain the determinants and consequences of individuals' media use is discussed. At the end, to examine and ensure the applicability of the media system dependency theory in the context of the Internet, the current adoptions of the theory in the Internet context are analyzed. The theoretical background developed in this chapter is used then in chapter 4 to construct the conceptual framework of this dissertation.

3.1 Technology Acceptance Research

Understanding the factors that influence the acceptance and use of information technologies has been one of the major streams of research in information system since 1980. After the advent of computers and introduction of various computer-based applications in the business realm with the goal to ease the workload and boost its affectivity and efficiency, information technology has become a decisive factor for the success of business operations. However, the advances were coupled with the problem of the low adoption and underutilization making the issue of the acceptance an enduring challenge in the system design and implementation. To overcome this challenge, practitioners needed to understand the true causes of the acceptance or rejection of a certain information system enabling them to decide about its implementation or to develop intervention measures to promote its acceptance. As a result, the need for studies to understand, explain, and predict the acceptance and use of information technologies has been born; the response of the academia to this need has led to the vast amount of research on the acceptance of information technologies.

As information technologies left the offices and reached a larger audience with products and services targeting individual consumers who contrary to business users could voluntarily decide to accept or reject them, this challenge has reached a new scale; especially for more radical technologies as ubiquitous information systems. However, there are plenty of studies addressing the individual level acceptance of information systems for different technologies and contexts; there is no one universal set of determinants which can explain the acceptance of all kind of technologies in any context. To emphasis the need for further studies in the individual technology acceptance for emerging information technologies and contexts, Venkatesh (2006), one of the well-known scholars in field, insists that "*stating that research on individual-level technology adoption is mature is an understatement*" (p. 497).

The term acceptance stems from a Latin term, recipere, which means to receive, "*to take what is offered. Thus, acceptance means that an individual must partake in an action to take what is offered*" (Schwarz, 2003, p. 33). In this context, acceptance is not the act of the use itself but just the precondition of use (Schwarz, 2003). Translating this into the information technology paradigm, acceptance expresses a form of an affirmative attitude or a behavior of subjects/individuals towards a certain object/information system to perform a certain task which the system is designed to support.

As said, the concept of acceptance captures just the notion of willingness to use and not the actual use; however, it is defined as a strong determinant of use. As Dillon and Morris (1996) state, "*obviously there is a degree of fuzziness here since actual usage is always likely to deviate slightly form idealized, planned usage, but the essence of acceptance theory is that such deviations are not significant; that is, the process of user acceptance of any information system for intended purposes can be modeled and predicted*" (p. 7). In information technology literature, various terms can be found for the concept of acceptance, a meta-analysis of studies for acceptance of information systems showed that the terms "adoption", "diffusion" and "acceptance" are used almost identical, however the term "adoption" is slightly more favored (M. D. Williams et al., 2009).

Tailoring to the objectives of this dissertation, acceptance in this work means the willingness of an individual to voluntarily use an in-store ubiquitous computing information system to get the benefits associated with such systems. The notion of voluntary use is quite important here as it puts the current work in contrast to the classical office-based task-related information systems.

Basically, there are two main streams of research in the field of technology acceptance; the first stream is concerned with the "objective features" of a technology causing its diffusion in the market and the second stream is concerned with the "subjective qualities" persuading its use by individuals.

The first stream is originated in the diffusion of innovation theory (Rogers, 2010, 1983). Rogers defines diffusion as the process by which an innovation is communicated over time and through the various channels to the members of a social system. Diffusion is therefore a special type of communication and addresses the dissemination of information dealing with new products or services. In marketing, diffusion research is used to explain and understand the development of novel product or service purchases over the course of time. Understanding purchase dynamics of a novel product enables marketers to influence the process for example by means of marketing tools. Examining a large amount of innovation studies, Rogers (1983) summarizes five main characteristics of an innovation which influence its diffusion rate, namely relative advantage, complexity, compatibility, trialability and observability; that is the extent of presence of these characteristics in a certain technology innovation is directly related to the extent of the acceptance of that technology innovation. The diffusion based acceptance focuses on the perceptions of the innovation itself rather than perceptions of using the innovation (Moore and Benbasat, 1991), which stresses its objective view.

The second stream of research on the acceptance and use of technological innovations is dedicated to the psychology of the user acceptance and built on the grand theories of social psychology, such as the theory of reasoned action (TRA) (Fishbein, 1967) and theory of planned behavior (TPB) (Ajzen, 1985). These theories are designed to explain the human behavior taking a holistic approach and therefore can be also applied to the acceptance of technological innovations. Here, acceptance is defined as a consequence variable in "*a psychological process that users go through in making decisions about technology*" (Dillon and Morris, 1996, p. 13).

Tailoring the TRA to the field of information technology resulted in advent of the famous technology acceptance model (TAM) (Davis, 1986). Since its introduction TAM has been the most prominent model in technology acceptance studies. According to a meta-analysis from 2009, TAM was the predominately used theory in information technology acceptance studies, however only 16% of studies were based on the innovation diffusion theory (M. D. Williams et al., 2009). The objective of this stream of research is to comprehend the dynamics of human decision making in the context of accepting or rejecting technology and to predict how individuals in a certain context will respond to new technologies and consequently to take necessary measures for its optimum acceptance.

Synthesizing the characteristics and objectives of each stream of research with those of this dissertation, the second stream of research is the most suitable theoretical platform for the purpose of the current dissertation:

- Firstly, the technologies under study in this dissertation are still in their infancy and not yet widely spread, so a process oriented approach of the diffusion theory is inappropriate for analyzing their acceptance.
- Secondly this dissertation in its core seeks to dig out the antecedent factors of acceptance of in-store ubiquitous computing-based information services at individual level. The

perspective of diffusion research which is market and object oriented versus individual user oriented (Verkasalo, 2009), keeps its usability in the individual user's technology acceptance limited. In this regard Dillon and Morris (1996) emphasize that "*while diffusion theory provides a context in which one may examine the uptake and impact of information technology over time, it provides little explicit treatment of user acceptance."* and further recommend *"as researchers seek to identify the factors that determine user acceptance of any information technology (…), the question of acceptance has come to be tackled more directly by researchers working outside the classical innovation diffusion tradition"* (p. 12). Therefore, the objectives of this dissertation fit better to the objectives of the second stream of research.

Hence, the remainder of this section is dedicated to review of relevant literature on technology acceptance models; starting from the origins, introducing the TAM and its major extensions and variations which are the most relevant for the purpose of current research, as well as analyzing the empirical studies which apply the technology acceptance models into the ubiquitous computing applications in physical stores.

3.1.1 The Origin of Technology Acceptance Models

As mentioned above, the origins of the most of the technology acceptance models are based on the two theories of "Theory of Reasoned Action" and "Theory of Planned Behavior". These two theories are related in a way that the latter is an extension of the former.

3.1.1.1 Theory of Reasoned Action

Theory of Reasoned Action (TRA) was first introduced in 1967 (Fishbein, 1967) and later revisited and refined by two psychologists, Ajzen and Fishbein (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975) as a result of their extensive research effort to integrate diverse theories and research streams in the attitude studies. As its name implies, theory of reasoned action builds on the notion of reasoned rather than automatic behavior in which "*people consider the implications of their actions before they decide to engage or not engage in a given behavior*" (Ajzen and Fishbein, 1980, p. 5).

TRA was created to predict the acceptance of information and recommendations for stimulating change in behaviors (Silva, 2007). Assuming a direct relation between the behavior intentions and actual behavior, TRA tries to understand a specific behavior by predicting the individual's intentions (Ajzen and Fishbein, 1973; Fishbein and Ajzen, 1975). "*Intentions are assumed to capture the motivational factors that influence a behavior*" (Ajzen, 1991, p. 181).

The objective of TRA was not only to predict the behavior but also understand the "*psychological determinants*" of a behavior, therefore the theory introduces two determinants for the intention (Ajzen, 1985, p. 12), namely attitude toward the behavior and subjective norm. As shown in Figure 5, attitude toward a behavior and subjective norm form the intention and intention in turn is the direct determinant of behavior (Ajzen and Fishbein, 1980).

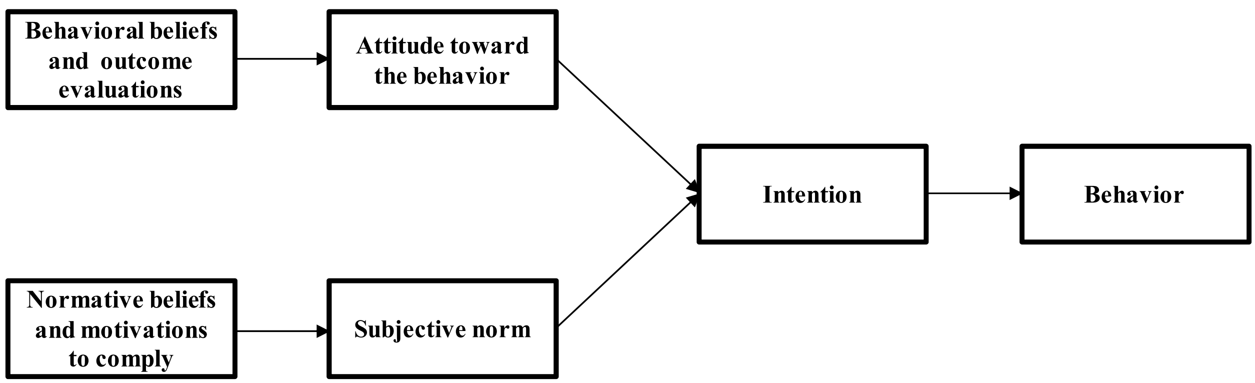


Figure 5: Schematic presentation of Theory of Reasoned Action (TRA) (Ajzen and Fishbein, 1980, p. 100)

The thread of behavior determinates in TRA doesn't stop at the attitude toward the behavior and subjective norm; TRA argues that the starting point for an individual to decide about performing a certain behavior or not is formation of beliefs regarding that behavior. A belief is "*the subjective probability of a relation between the object of the belief and some other object, value, concept, or attribute*"(Fishbein and Ajzen, 1975, p. 131). This subjective relationship between the object of belief and some other object which is in fact the individual's information about the object can be formed through direct observation (descriptive belief), perceived valid information sources (informational belief), or through the inference from other beliefs (inferential) (Fishbein and Ajzen, 1975).

As an individual's beliefs toward an object are formed, she concurrently attains an attitude toward that object; therefore, a positive attitude is the outcome of the belief that performing of a certain action with high (low) probability will result in positive (negative) consequences. Respectively, a negative attitude is the product of a belief that a behavior with high (low) probability will have negative (positive) consequences. In other words, the attitude of an individual toward a behavior "*correspond to the favorability or unfavorability of the total set of consequences, each weighted by the strength of the person's beliefs that performing the behavior will lead to each of the consequences*" (Ajzen and Fishbein, 1980, p. 67). Thus different individuals who expect the same consequences may have different attitudes towards an act depending on the assessment of the desirability of the consequences.

The same logic applies to the subjective norm; subjective norm is a function of some beliefs, in this case called normative beliefs (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 2010). Subjective norm is defined as "*an individual's perception* (belief) *that most people who are important to her think she should perform a particular behavior*" (Fishbein and Ajzen, 2010, p. 131). This is a measure of perceived social pressure to perform or to refrain from a behavior in question. It results from aggregation of the perceived expectations of reference persons or groups regarding a certain behavior and willingness to behave according to these expectations. So the beliefs concerning what different people or groups consider correct or incorrect behavior (injunctive norms) as well as beliefs about what important others are actually doing (descriptive norms) are the informational foundation to form an individual's subjective norm (Fishbein and Ajzen, 2010).

TRA also considers so-called external factors such as situational factors, demographic variables or personality traits to have indirect effects on behavior through their effects on central variables of the theory (Ajzen and Fishbein, 1980). As depicted in Figure 6, external variables may influence the behavior through individuals' beliefs regarding the consequences of a certain behavior and their evaluation as well as the beliefs concerning the referents' expectations along with the willingness to comply with a certain referent.

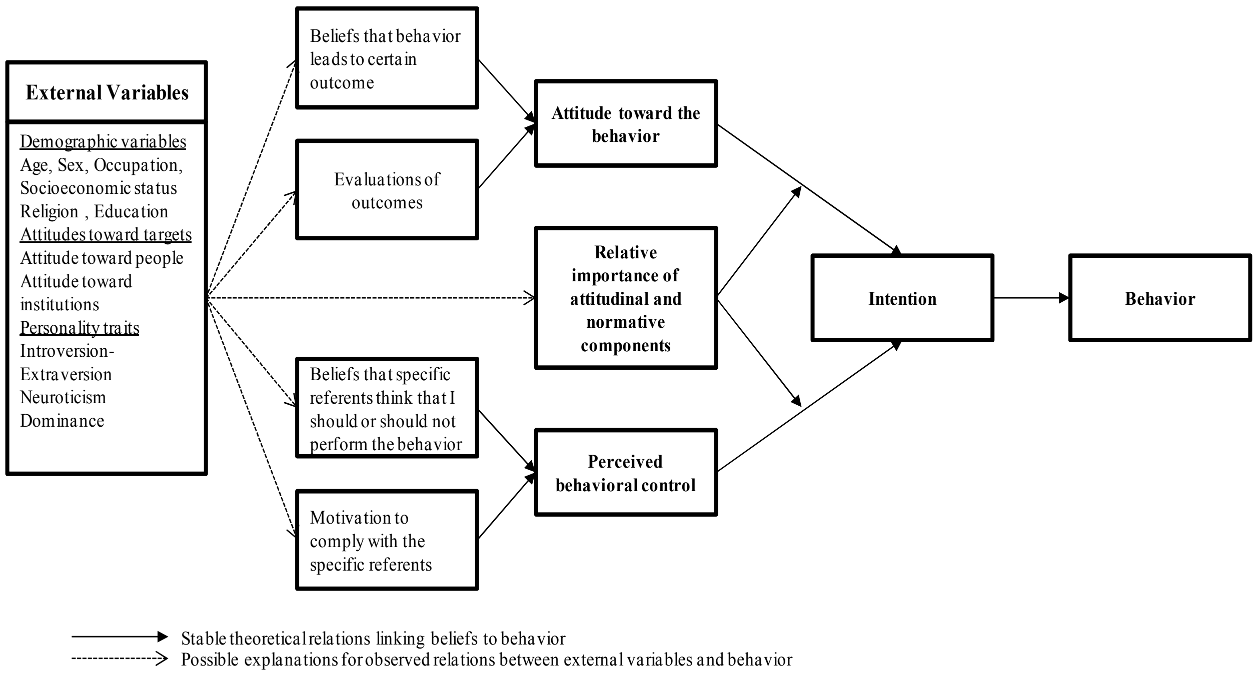


Figure 6: A detailed schematic presentation of TRA including the external variables (Ajzen and Fishbein, 1980, p. 84)

Although TRA predicts the volitional behavior quite well, its performance is rather limited when it comes to the cases in which individuals cannot decide freely for their actions or may not have total control over the potential obstacles which can prevent them from performing an intended behavior (Ajzen, 1985). In this regard, TRA assumes that performing a behavior is not related to opportunities and there is no pre-requirement for resources such as time, financial resources, skills or social support to perform a behavior. Therefore, later the theory has been revisited and extended to cover its limitations which resulted in the advent of the Theory of Planned Behavior.

3.1.1.2 Theory of Planned Behavior

In response to the limitations of the TRA, Ajzen (1985) introduced an extended version by adding a control factor to the original TRA. Named as Theory of Planed Behavior (TPB), this theory assumes that besides attitude toward the behavior and subjective norm, perceived behavioral control is a direct determinant of the behavioral intention (Ajzen, 1991, 1985), as shown in Figure 7.

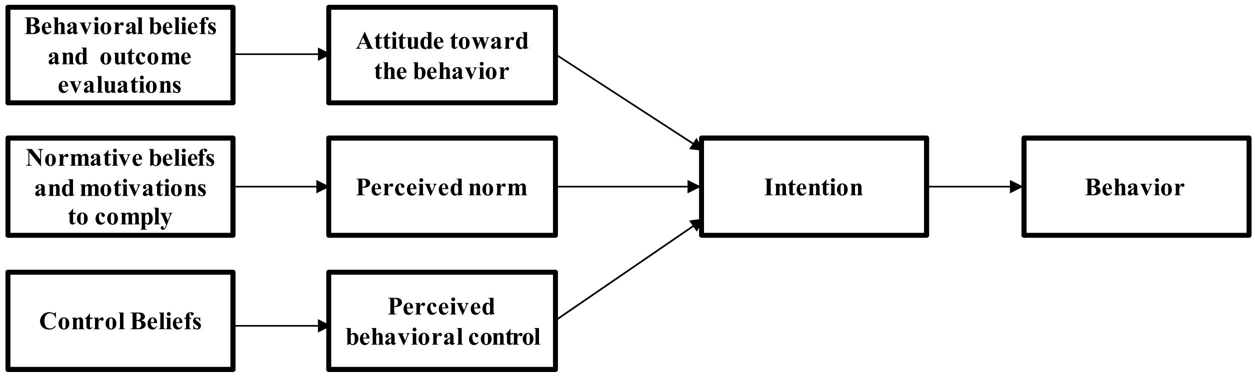


Figure 7: Schematic presentation of Theory of Planned Behavior (TPB) (Ajzen, 1991, p. 182)

Perceived control embodies the potential internal and external interfering factors shaping an individual's perception concerning the ease or difficulty of performing a certain behavior (Ajzen, 1991). In a recent updated version of the theory, Fishbein and Ajzen (2010) define the perceived behavioral control as "*people's perception of the degree to which they are capable of, or have control over, performing a given behavior*" (p.64). Perceived behavioral control is often described as similar to the concept of self-efficacy (Bandura, 1977) that is "*a judgment of one's ability to organize and execute given types of performances*" (Bandura, 1997, p. 21) with a distinction that it also includes the external control factors (Lim and Dubinsky, 2005). However in empirical studies, the perceived difficulty of performing an act (self-efficacy) turned out to be a better predictor of the behavioral intentions and behavior than the controllability (Ajzen, 2001).

Having integrated the control factor into the theory, TPB even modifies the notion of intention; it is no longer merely the subjective probability of performing a behavior but also the amount of effort that a person is willing to invest performing a certain behavior. In other words in the context of TPB, intentions "*are indications of how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behavior*" (Ajzen, 1991, p. 181).

Identical to the notion of beliefs in TRA, control beliefs play a central role in TPB; perceived behavioral control is a function of control beliefs that are the amount of resources, skills and options which an individual believes to possess (Ajzen, 1985; Yzer, 2012); internal factors such as self-discipline, willpower, constrains and habits as well as external factors such as unexpected events or behavior of other people are the additional influencing factors of control beliefs (Fishbein and Ajzen, 2010). In short, the greater the intention of the person to perform an act and the greater his control over internal and external interfering factors, the greater the probability that one would perform the planned behavior. Since its advent, TPB has been one of the most influential models in prediction of individual behavior. However it has been often criticized for its rational man assumption and consequently "*not taking sufficient account of cognitive and affective processes that are known to bias human judgments and behavior*" (Ajzen, 2011, p. 1115). Although the affective and cognitive factors are not included in the central constructs of TPB, their indirect influence on behavior have been considered by integrating the background factors which influence the belief constructs in the theory (Ajzen, 2011) (see Figure 8). Ajzen (2011) argues that TPB doesn't hold the rational man assumption by comprising beliefs mirroring an individual's information concerning the performance of a certain behavior which could be inaccurate, incomplete or emotionally biased. Independent from the quality of beliefs, being it biased or unbiased, irrational or rational, attitudes and thus intentions and behaviors are consistent with these beliefs (Geraerts et al., 2008). Figure 8 shows an elaborated version of TPB, including the background factors and their influence on formation of beliefs.

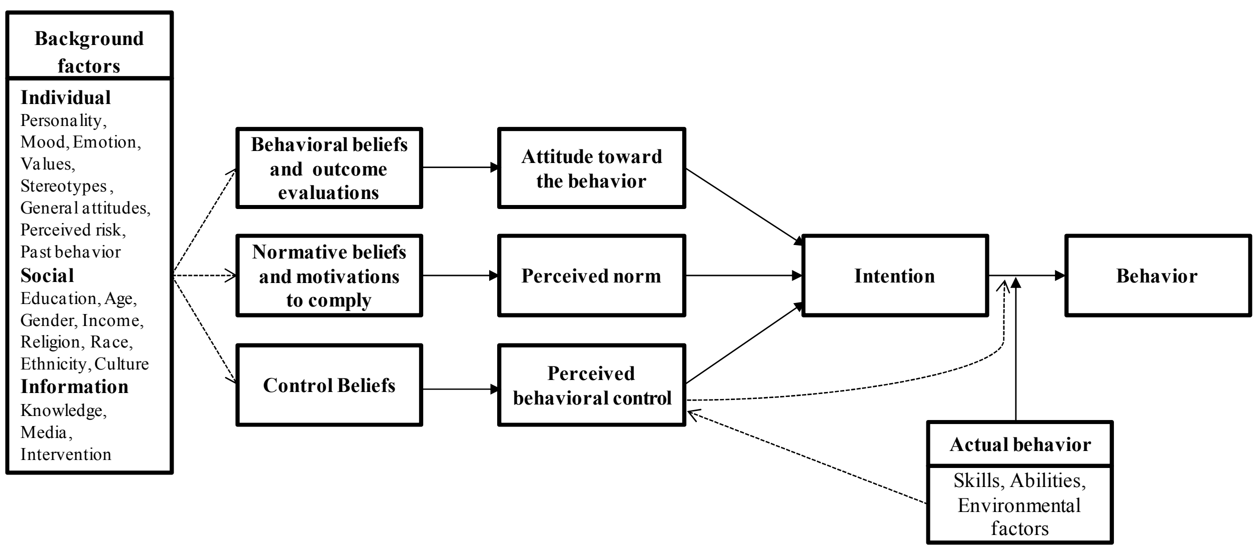


Figure 8: A detailed schematic presentation of TPB including the background factors (Fishbein and Ajzen, 2010, p. 22)

Both the TRA and TPB have been applied in numerous studies to predict intentions and actual use of the information systems (Agarwal, 2000; Armitage and Conner, 2001; Davis et al., 1989; Khalifa and Cheng, 2002; Malek, 2011) and in many cases their validity for explanation of the reasoned and planned behaviors have been confirmed with TPB having a better explanatory power than TRA. However, due to the general approach of the TRA and TPB, usually it has been necessary in empirical studies to tailor the model constructs to the research context and the behavior in question.

3.1.2 Technology Acceptance Model (TAM)

As mentioned above, due to the general approach of the TRA and TPB, researchers often had to tailor the model constructs to their research context and the behavior in question. By doing so, Davis (Davis, 1993, 1989, 1986; Davis et al., 1989) introduced the technology acceptance model (TAM); building on theoretical foundation of TRA, TAM offers a unified set of constructs and indicators applicable for describing and understanding an individual's acceptance of information systems for different technologies and user populations. Since its introduction, TAM has been one of the most influential models in information systems field and much of the technology acceptance studies are based on TAM or one of its various extensions (Lee et al., 2003).

As shown in Figure 9, adopting the TRA to the domain of information technology, Davis replaced the TRA's attitudinal determinants with two other predictors of behavioral intention i.e., perceived usefulness and perceived ease of use. Perceived usefulness is defined as "*the degree to which an individual believes that using a particular system would enhance his or her job performance*" and perceived ease of use as "*the degree to which an individual believes that using a particular system would be free of physical and mental effort*" (Davis, 1986, p. 26).

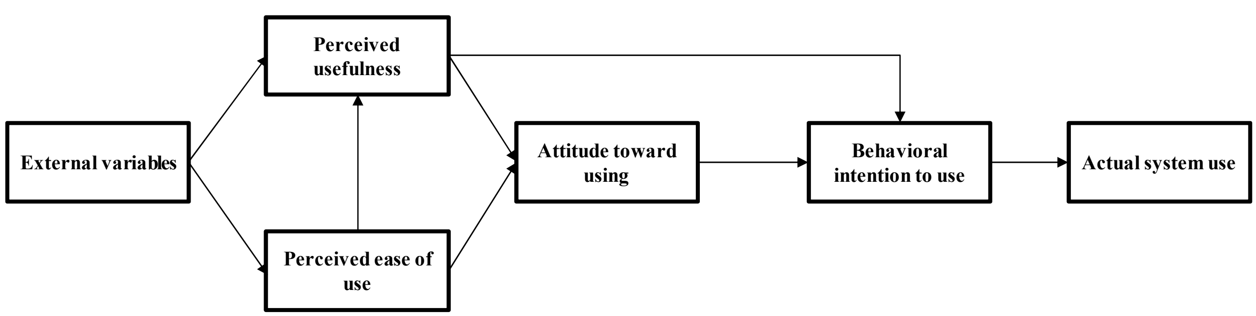


Figure 9: Schematic presentation of Technology Acceptance Model (TAM) (Davis et al., 1989, p. 985)

Inheriting from TRA, TAM posits that the actual system use is a function of behavioral intention to use. But unlike TRA, behavioral intention is dependent on both attitudes toward using and perceived usefulness. Davis justifies the direct relationship between the perceived usefulness and behavioral intention by referring to the assumption that people build their intention to use an information system by cognitive assessment of potential performance improvements (Bagozzi, 1982). Therefore, if a system improves the performance of a user, regardless of her attitude toward the using, the resulting benefits can drive the use intention (Konana and Balasubramanian, 2005). Furthermore, as the notion of the attitude in TRA covers only the affective aspects, the direct relationship between the perceived usefulness and behavioral intention adds an unambiguous performance oriented or cognitive aspect to the whole model.

Usefulness and ease of use beliefs are the most important components of the information system acceptance, as they are easy to manipulate through external factors such as system features, training, and user support consultants (Davis et al., 1989). Therefore, TAM further theorizes that the influences of external factors on attitude toward using are through perceived usefulness and perceived ease of use. Additionally perceived usefulness is determined by perceived ease of use based on the logic that "*other things being equal, the easier the system use the more useful it can be*" (Venkatesh and Davis, 2000, p. 187).

Later, Davis et al (1989) proposed a more powerful version of TAM; based on the results of a longitudinal study on intentions to use a specific system, they have removed the attitude construct from the original model since the construct at best "*only partially mediated*" the relationships between beliefs and intentions (p. 999). After introducing this new conceptualization of the TAM, both Davis himself and subsequent research suggested that however TAM can indeed serve as basis for technology acceptance studies, it needs to be refined and extended in regard to different information technologies to improve its explanatory power (Adams et al., 1992; Davis, 1989; Davis et al., 1989). So it comes as no surprise that reviewing technology acceptance literature, different variations of TAM can be found. However, despite many enhancements and adjustments, the basic concept of the TAM, illustrated in Figure 10, still remains the foundation in design of the majority of technology acceptance models.

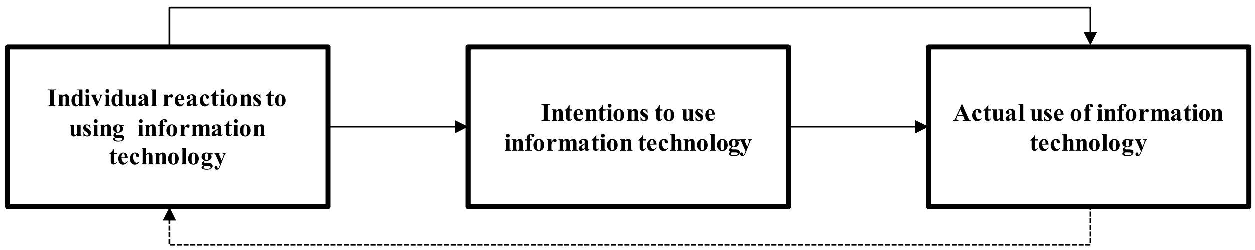


Figure 10: Schematic presentation of the basic concept underlying user acceptance models (Venkatesh et al., 2003, p. 427)

The development of TAM can be divided into four phases, namely, introduction, validation, extension, and elaboration (Lee et al., 2003). The introduction phase was consisted of replication and comparison studies to verify the model's parsimoniousness as well as superiority to other models (Lee et al., 2003). Through this phase many studies could successfully validate the consistency of TAM's explanatory power with regard to different technologies and in different settings (e.g. Adams et al., 1992; Davis, 1993).

While TAM was empirically validated by many studies showing superior parsimoniousness and explanatory power when compared with other models (e.g. King and He, 2006; Ma and Liu, 2004; Schepers and Wetzels, 2007; Mathieson, 1991; Yousafzai et al., 2007a; Shankar et al., 2003; Davis et al., 1989), another stream of research was concerned with the validity of TAM's measurement instrument in different technologies, situations, and tasks (e.g. Barki and Hartwick, 1994; Davis and Venkatesh, 1996; Hendrickson et al., 1993; Lee et al., 2003; Segars and Grover, 1993; Szajna, 1994). The studies in validation period could more or less agree on the fact that TAM instruments were powerful, consistent, valid, and reliable (Lee et al., 2003).

Although TAM proved to be exceptionally robust thanks to the substantial theoretical and empirical support, several studies suggest that the model's parsimonious approach tends to limit its ability to provide a deeper understanding of the factors contributing to technology acceptance (Benbasat and Barki, 2007; Lee et al., 2003; Mathieson, 1991; Venkatesh, 2000; Yousafzai et al., 2007b). As a matter of fact, while usefulness and ease of use proved to be fundamental determinants of usage intention (Adams et al., 1992), TAM overlooks other important beliefs as normative and affective beliefs and does not provide a mechanism for their inclusion (Benbasat and Barki, 2007). In addition, TAM only focuses on direct determinants of use overlooking the prior/external factors influencing the formation of ease of use and usefulness beliefs and consequently how they can be influenced to promote increased usage (Yousafzai et al., 2007a). Furthermore TAM's explanatory power declines when not applied in the workplace situations (Yousafzai et al., 2007b).

Responding to TAM's shortcomings, since 1994 researchers have made their extended models of original TAM by introducing additional variables, linking TAM to other theories such as innovation diffusion theory or TRA, and looking for antecedents of major TAM constructs (Lee et al., 2003). Even in the context of consumer oriented innovations, numerous extensions of TAM have been introduced trying to tailor the model to consumer technology acceptance for example by adding personality traits and shopping motives (O'Cass and Fenech, 2003), involvement (Koufaris, 2002), and computer affinity (Stern et al., 2008).

The results of studies in extension phase enriched the original model, but at the same time generated numerous model variations and raised new questions and limitations. To synthesize the results and resolve the limitation of these studies, a new class of research has emerged taking the TAM based research to the elaboration phase (Lee et al., 2003). The efforts in this phase lead to the introduction of further TAM based salient models as UTAUT (Venkatesh et al., 2003) and set the groundwork for further research.

Having discussed TAM and its different development phases, the remainder of this section is dedicated to the review of extensions and elaborations of TAM which are the most relevant for the theoretical foundation of current dissertation.

3.1.2.1 Extension of TAM by Social Factors

Although TAM was built based on TRA which affirmed that both attitude towards an act and subjective norms are the antecedents of the intention, it overlooked the effect of subjective norms in its original form. Yet, the importance of social context on the formation of individual's perception regarding a certain object has been emphasized by social psychologists (Robertson, 1989; Triandis, 1979). Even Davis himself has noted that it is essential to consider the subjective norm in technology acceptance studies (Davis, 1986; Davis et al., 1989). Being aware of its importance, different scholars have tried to include the concept of subjective norm into TAM, resulting in conception of different constructs and relationships.

Malhotra and Galletta (1999) for the first time introduced an extension of TAM including the notion of social influence. As shown in Figure 11, they have set up a construct labeled as psychological attachment made up of different social aspects to capture the concept of social influence which directly affects the behavioral intention. The theoretical basis for this is provided by Kelman (1958), he distinguishes three different processes of social influence namely compliance, identification and internalization. Compliance refers to an influence when a person adopts a behavior not because she wants it herself but with an incentive of receiving a reward. Identification is referred to an influence which occurs when an individual accepts to follow other person's perception as she wills to keep or build a relationship to other person or group. Internalization occurs when a person accepts influence since it is congruent with her own value system.

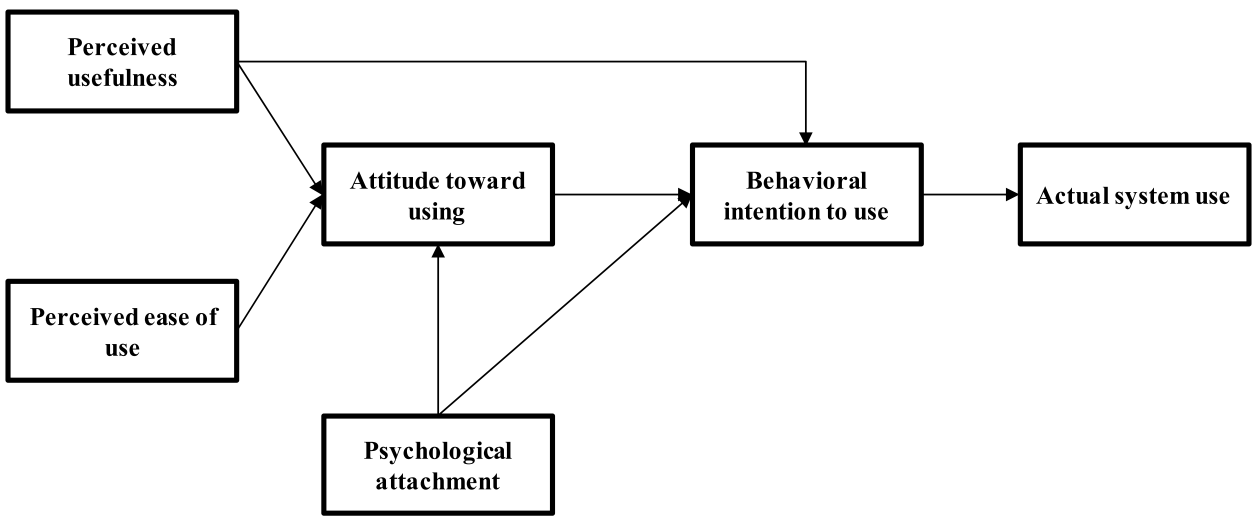


Figure 11: Schematic presentation of TAM extended to account for social influences (Malhotra and Galletta, 1999, p. 4)

Based on a survey of 208 people, Malhotra and Galletta could conclude that social influences play an important role in acceptance of new information technology products; results show that the sense of compliance has a negative impact on the attitude towards use of a new information technology. In contrast, when social influences generate feelings of internalization and identification, they have a positive influence on attitude toward use. However, the study did not deliver statistically significant results between the social influences and behavioral intention. Hence social factors influenced the behavior intention only indirectly through attitude. Malhotra and Galletta recommend that while introducing new information systems the focus should be on the development of positive attitudes towards using by developing psychological attachment which would ultimately lead to acceptance behavior. At the same time, they note the need for more research in this area.

Later, Venkatesh and Davis (2000) introduced a theoretical extension of the basic TAM referred as TAM2. As mentioned in previous section, many studies suggest that the original TAM's parsimonious approach tends to limit its ability and call for the extension of model by including other components which can serve as determinants of the TAM's main constructs, usefulness and ease of use. Taking into account that perceived usefulness is the most important determinant of usage intention, TAM2 integrated some new theoretical constructs into original TAM as antecedents of perceived usefulness and intention of use. These new constructs captured the notion of social influence and cognitive instrumental processes. The model covers the notion of social influence processes by constructs of subjective norm, image and voluntariness and the notion of cognitive instrumental processes by constructs of job relevance, output quality, result demonstrability as well as perceived ease of use.

Figure 12 shows the proposed TAM2. The model particularly explains the role of social influence on information systems acceptance and use. In this model, consistent with the TRA (Fishbein and Ajzen, 1975) and TPB (Ajzen, 1991), the subjective norm is defined as direct determinant of intention to use. This direct relationship was justified following the same rationale as TRA that "*people may choose to perform a behavior, even if they are not themselves favorable toward the behavior or its consequences, if they believe one or more important referents think they should, and they are sufficiently motivated to comply with the referents*" (Venkatesh and Davis, 2000, p. 187).

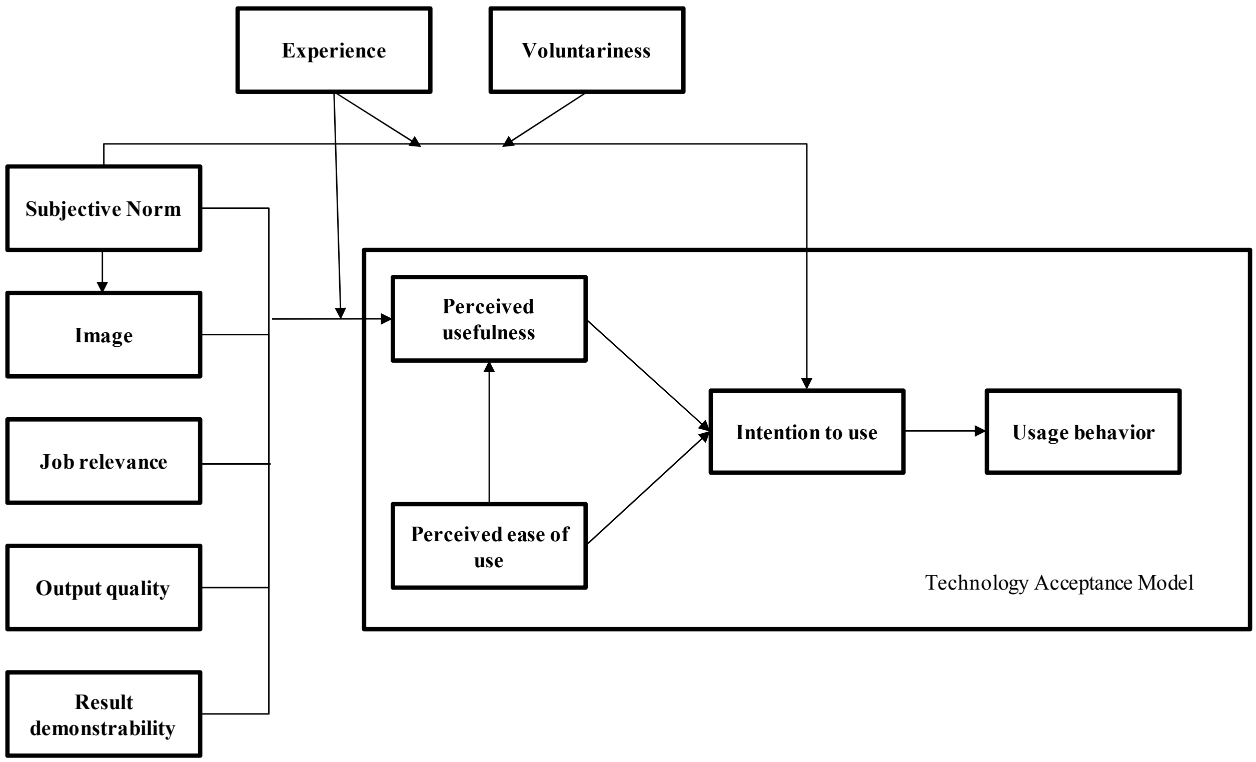


Figure 12: Schematic presentation of TAM2 – an extension of TAM (Venkatesh and Davis, 2000, p. 188)

Due to the conflicting results of previous studies on the effect of subjective norm on use intention, no effect (Davis et al., 1989; Mathieson, 1991) versus significant effect (Taylor and Todd, 1995a), Davis (1989) emphasized the need for more research on "*conditions and mechanisms governing the impact of social influences on usage behavior*" (p. 999). To do so, following the approach of Hartwick and Barki (1994), TAM2 posited voluntariness as a moderating variable of the direct relationship between the subjective norm and intention to use; so that relationship will only exist when the system use is perceived mandatory. This is also referred as compliance effect or compliance with social influence as even in mandatory cases, if a user is unwilling to comply, the relationship will not operate (Hartwick and Barki, 1994).

In addition, TAM2 assumes that this relationship becomes weaker as the user becomes more experienced. Similar to Malhotra and Galletta's model, TAM2 used the compliance, identification and internalization processes of social influences. In TAM2, in addition to the direct relationship between subjective norm and intention to use, subjective norm can influence usage intentions through perceived usefulness which is justified by internalization effect. The direct effect of subjective norm on image is on the other hand referred as identification effect which implies that one will perceive a system useful when she believes that using the system will improve her image among her social group.

In regard to cognitive instrumental process, TAM2 assumes that the perceived usefulness of a system is dependent on the individuals' perception of the suitability of system capabilities to their needs. This assumption is valid for all cognitive instrumental process variables, job relevance, output quality, and result demonstrability (Venkatesh and Davis, 2000); if the user could match them with her needs, then the system will be perceived as useful.

TAM2 was tested in organizational context at three points in time; four organizations have been included in the study, two for voluntary and two for mandatory use of information systems. All TAM relationships as well as the most of the TAM2 relationships, except output quality, were validated. The results showed that the new model explained 40-60% of the variance in perceived usefulness and 34-52% of the variance in intention to use (Venkatesh and Davis, 2000). One of the most important contributions of TAM2 was including the notion of social influence in the technology acceptance model and showing a direct effect of subjective norm on intention to use.

Several other studies could empirically support the direct positive influence of social factors on usage intention (e.g. Hsu and Lin, 2008; Hsu and Lu, 2004; Mun et al., 2006; Venkatesh et al., 2012, 2003) .Table 7 summarizes the different labels used in the literature to capture the notion of social response of individuals associated with system use. These constructs were chosen if they satisfied the following two criteria:

- A construct/label which captures a holistic vision of social response, therefore excluding factors such as image and need for uniqueness.
- Inclusion of the social factor was in line with an attempt to extend and improve the TAM (TAM was the baseline model in the studies) and a direct significant relationship between the social factor and intention to use could be empirically supported.

Table 7: Factors capturing normative beliefs

Belief structure	Objective	Selected constructs	Studies
Normative beliefs	To capture the essence of perceived social influences posed to an individual by the social surrounding regarding use of a certain system	Social influence	(Venkatesh et al., 2012, 2003)
		Subjective norm	(Mun et al., 2006; Venkatesh and Davis, 2000)
		Social factors/norms	(Hsu and Lin, 2008; Hsu and Lu, 2004)
		Psychological attachment	(Malhotra and Galletta, 1999)

3.1.2.2 Extension of TAM by Affective Factors

Despite TRA and TPB which locates the individual on an affective and cognitive bipolar evaluative dimension while deciding about the performing of a certain behavior (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 2010), in TAM the component of the behavioral beliefs has been translated into two merely cognitive factors of perceived usefulness and ease of use. As a result, in technology acceptance studies, the cognitive or utilitarian perspective which is the answer to the question of “how useful a system is?” has been included since the introduction of original TAM; however, the affective perspective which respectively is the answer to the question of “how enjoyable the use a certain system is?” had long been neglected.

The notion of bidimensional attitudes has been suggested in consumer research literature (Batra and Ahtola, 1990; Childers et al., 2001; Holbrook and Hirschman, 1982); overall the motivation of consumers can be classified in two, cognitive and affective dimensions (McGuire, 1976). This two-dimensional view of consumer attitude has been supported by many scholars from different disciplines as sociology, psychology and economics (Clore and Schnall, 2005; Lewis et al., 2010). In consumer research literature, these dimensions are usually mentioned as hedonic and utilitarian components of consumer choice. Utilitarian and hedonic components are not mutually exclusive, but both contribute to consumer behavior (Batra and Ahtola, 1990).

Furthermore, a stream of research in human-computer interaction dedicated to the role of emotion in usage of computers stresses that, as the emotions are the essential part of being human, individuals cannot put away their emotions and work only rationally and effectively with computers (Brave et al., 2005; Brave and Nass, 2003; Norman, 2004; Norman et al., 2003). Therefore, a decision for or against an information system can be as well influenced by user's hedonic motivation.

As a response to the importance of the affect in technology usage and acceptance, many scholars tried to add the notion of affect into the technology acceptance model; this resulted in the rise of a group of differently labeled constructs with an almost identical goal of capturing the emotional side of technology use. Davis et al. (1992) for the first time introduced an affective factor called enjoyment to the original TAM to cover the notion of intrinsic motivations versus extrinsic motivations. Borrowing from the motivation theories, intrinsic motivation refers to the performance of an activity just because of the process of performing whereas extrinsic motivation refers to the performance of an activity because of the value of its consequences (Davis et al., 1992). Empirically testing their new model in workplace context, they could show that enjoyment has a significant direct effect on intention to use.

Later, Agarwal and Karahanna (2000) introduced a new multi-dimensional construct named cognitive absorption compiling three different concepts from individual psychology, namely absorption (Tellegen, 1982), state of flow (Csikszentmihalyi, 2014) and the notion of cognitive engagement (Webster and Ho, 1997). This multi-dimensional construct captured the state of deep involvement with software and enjoyment has been defined as one of its dimensions. Placing the cognitive absorption as an external variable in TAM, they hypothesized that cognitive absorption has a positive relationship with perceived usefulness and ease of use. In addition, playfulness as an extra affective factor was a determinant of cognitive absorption. The model was tested in the context of World Wide Web and results showed a significant relationship between the cognitive absorption and intention to use as well as playfulness and cognitive absorption.

Furthermore, Van der Heijden (2004) investigated the validity of TAM in utilitarian and hedonic information systems. Similarly, building on the motivational theory, the study could show that for hedonic systems, perceived enjoyment and perceived ease of use were stronger predictors of intention to use than perceived usefulness.

Most prominently, Venkatesh and Bala (2008) have introduced a new version of technology acceptance model referred as TAM3. As illustrated in Figure 13, the new model combined

TAM2 with a model of perceived ease of use determinants (Venkatesh, 2000). Whereas major contribution of TAM2 was introducing the influencing factors of perceived usefulness, particularly, subjective norm, TAM3 introduced determinants of ease of use.

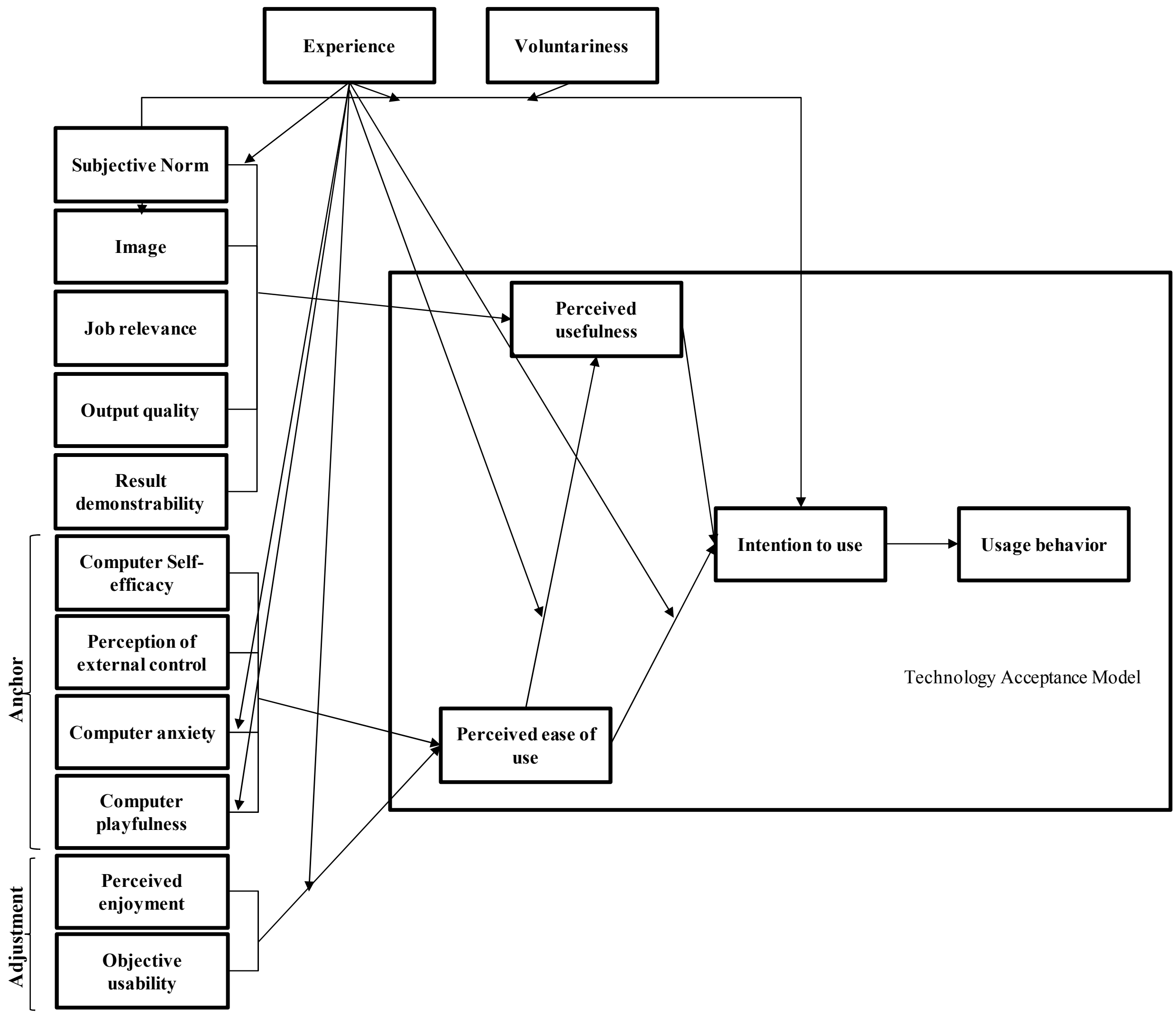


Figure 13: Schematic presentation of TAM3 – an extension of TAM (Venkatesh and Bala, 2008, p. 280)

Grounding on anchoring and adjustment heuristics (Tversky and Kahneman, 1973), in his model of perceived ease of use determinants, Venkatesh (2000) divided the influencing factors of ease of use in two anchor and adjustment variables; anchor variables which are related to individual's original beliefs are computer self-efficacy, perceptions of external control, computer anxiety, and computer playfulness. Adjustment variables which are related to individual's experience based adjustments of original beliefs are perceived enjoyment and objective usability; these variables become especially important when user's experience does not match with the original beliefs.

Through including the variables of computer playfulness, computer anxiety, and perceived enjoyment, TAM3 has integrated the affective variables into TAM. Venkatesh and Bala (2008) have tested their model in organizational context. The results confirmed the relationships between affective variables on perceived ease of use; the influence became stronger with increasing experience. The determinants of perceived ease of use could explain up to 52% of the variance and the determinants of perceived usefulness up to 67% of the variance. TAM3 could explain up to 53% variance in behavioral intention and up to 36% variance in usage behavior (Venkatesh and Bala, 2008).

Furthermore, in consumer context, Kulviwat et al. (2007) developed a new model by integrating affective components namely pleasure, arousal, and dominance of PAD theory (Mehrabian and Russell, 1974). This model, referred as consumer acceptance of technology (CAT), could explain 53% of the variance of intention, which correspond to up to 38% of improvement compared to TAM. Concerning the affective variables, except dominance, pleasure and arousal were significant predictors of attitudes. The empirical results showed that the higher the degree of pleasure and arousal of a consumer regarding a new technology, the more positive the attitude toward the adaption. Later Nasco et al. (2008) revised the CAT model especially because dominance had not shown the expected results in the previous model. They integrated two new factors, namely social influence and task type as moderators into the model; the empirical results showed that both in utilitarian and hedonic tasks, affective factors play an important role in usage intention of the individuals. Figure 14 provides a schematic presentation of the CAT model.

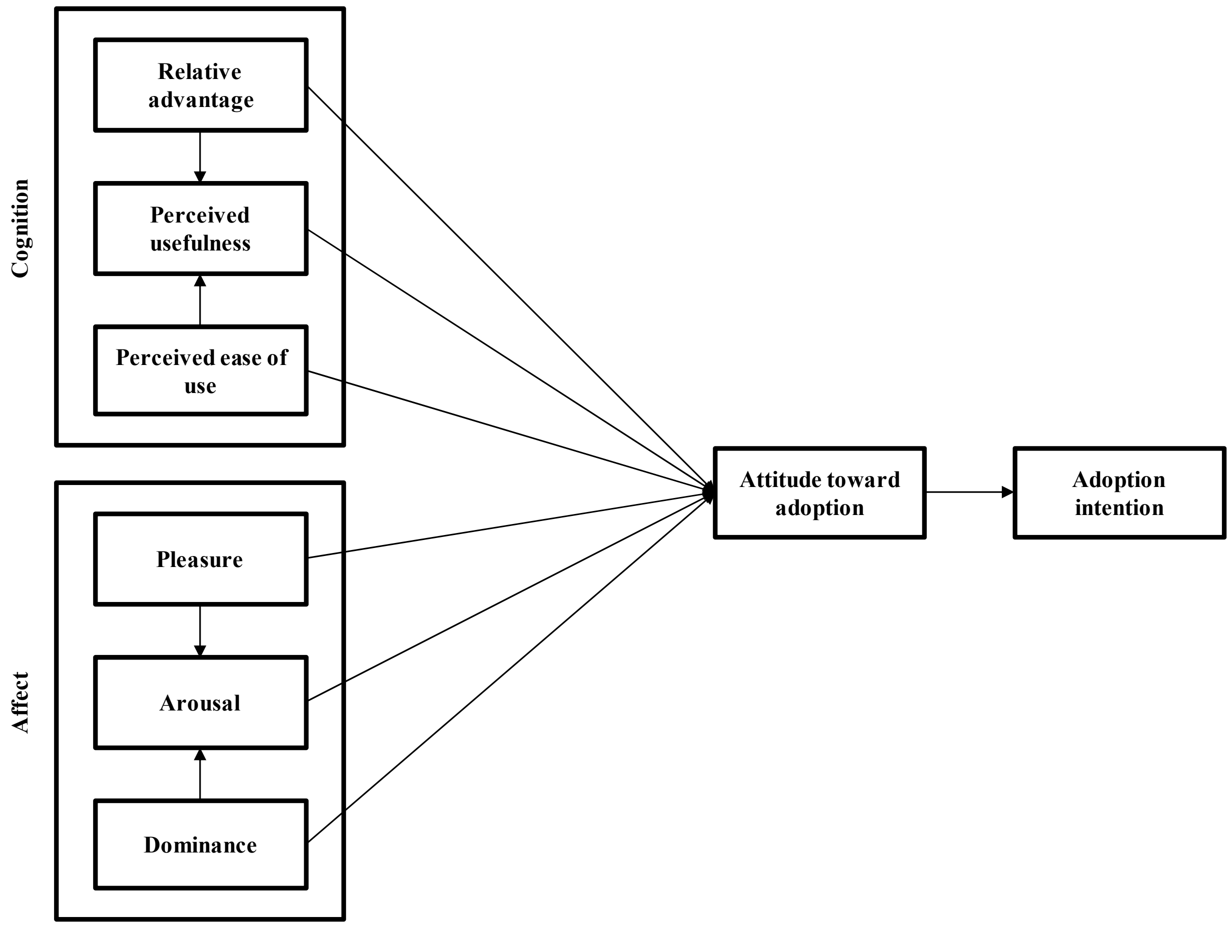


Figure 14: Schematic presentation of Consumer Acceptance of Technology (CAT) (Kulviwat et al., 2007, p. 1064)

Several other studies could empirically support the direct influence of affective factors on usage intention (Brown and Venkatesh, 2005; Chang and Cheung, 2001; Koufaris, 2002; Moon and Kim, 2001; Thong et al., 2006). Table 8, summarizes the different labels used in the literature to capture the affective response of individuals associated with system use. These constructs were chosen if they satisfied the following two criteria:

- A construct/label which captures a holistic vision of emotional response, therefore excluding factors such as satisfaction, arousal, pleasure, and playfulness.
- Inclusion of the affective factor was in line with an attempt to extend and improve the TAM (TAM was the baseline model in the studies) and a direct significant relationship between the affective factor and intention to use could be empirically supported.

Table 8: Factors capturing affective beliefs

Belief structure	Objective	Selected constructs	Studies
Behavioral beliefs: affective outcomes	Capture the emotional experience of an individual associated with an information system usage	Enjoyment/Perceived enjoyment	(Davis et al., 1992; Igbaria et al., 1995; Koufaris, 2002; Li, 2011; Teo et al., 1999; Thong et al., 2006; van der Heijden, 2004; Wen et al., 2011)
		Affect/Affect toward use	(Chang and Cheung, 2001; Goodhue and Thompson, 1995)
		Hedonic motivation	(Raman and Don, 2013; Venkatesh et al., 2012)

3.1.2.3 Elaboration of TAM – Unified Theory of Acceptance and Use of Technology (UTAUT)

The vast variety of models produced through the course of the research in acceptance of information systems made the model choice difficult for researchers. By an attempt to overcome this problem, Venkatesh et al. (2003) synthesized the core conceptually similar intention determinants of the eight prominent technology acceptance models in a Unified Theory of Acceptance and Use of Technology (UTAUT). In UTAUT, in addition to the original technology acceptance model, theory of reasoned action (discussed in section 3.1.1.1), and theory of planned behavior (discussed in section 3.1.1.2), five other models have been used:

- An adapted version of the social cognitive theory (Bandura, 1986) to the use of computer systems proposed by Compeau and Higgins (1995), in which performance and personal outcome expectations, self-efficacy as well as affect and anxiety influence the use behavior.
- The motivational model (Davis et al., 1992), which suggest that the adoption and use of new technologies are dependent on two factors, extrinsic and intrinsic motivation. The extrinsic motivation is based on the expected positive consequences of performing a certain behavior. Intrinsic motivation, however, is based on an interest in the performing an activity itself. In this model the notion of extrinsic motivation is captured by perceived usefulness and intrinsic motivation by enjoyment associated with the use.

- The combined TAM and TPB (Taylor and Todd, 1995a), which extends the theory of planned behavior by integrating the technology acceptance model constructs, perceived usefulness and ease of use.
- The model of PC Utilization (Thompson et al., 1991), which suggest six determinants for the computer use in professional context: Job fit and complexity of the technology, long-term consequences of the use, affect, social factors and facilitating conditions.
- An adopted version of innovation diffusion theory (Rogers, 1983) to the use of individual technology acceptance by Moore and Benbasat (1991) which postulates that 7 characteristics of innovation namely relative advantage, ease of use, image, visibility, compatibility, results demonstrability and voluntariness of use are determinates of technology acceptance.

As shown in Figure 15, based on an empirical comparison of the eight models Venkatesh et al. (2003) identified four constructs having a direct effect on intention to use or use behavior namely performance expectancy, effort expectancy, social influence, and facilitating conditions. Similar to the concept of usefulness, performance expectancy is a measure of the user's belief that using a system will increase her job performance. Effort expectancy indicates the degree of ease associated with the use of system. The social influence identifies the influence of important others on user's system use decision and facilitating conditions are defined as a measure of the user's belief that an organizational and technical infrastructure is available to support the user. The new unified model postulates that the strength of each relationship is dependent on the individual factors of age, gender and experience as well as voluntariness of use.

The model was empirically tested using data from four organizations and additionally cross-validated using data from two extra organizations. The empirical test of the UTAUT in organizational context showed that the model could deliver significantly better results than each of the eight original models; the researchers were able to explain 70 % of variance in usage intention and 48% in usage itself. The UTAUT also confirms the importance of social influences in user's behavioral intention; however, it also shows that their effect is dependent on the user's experience that is the effect decreases with increasing user experience.

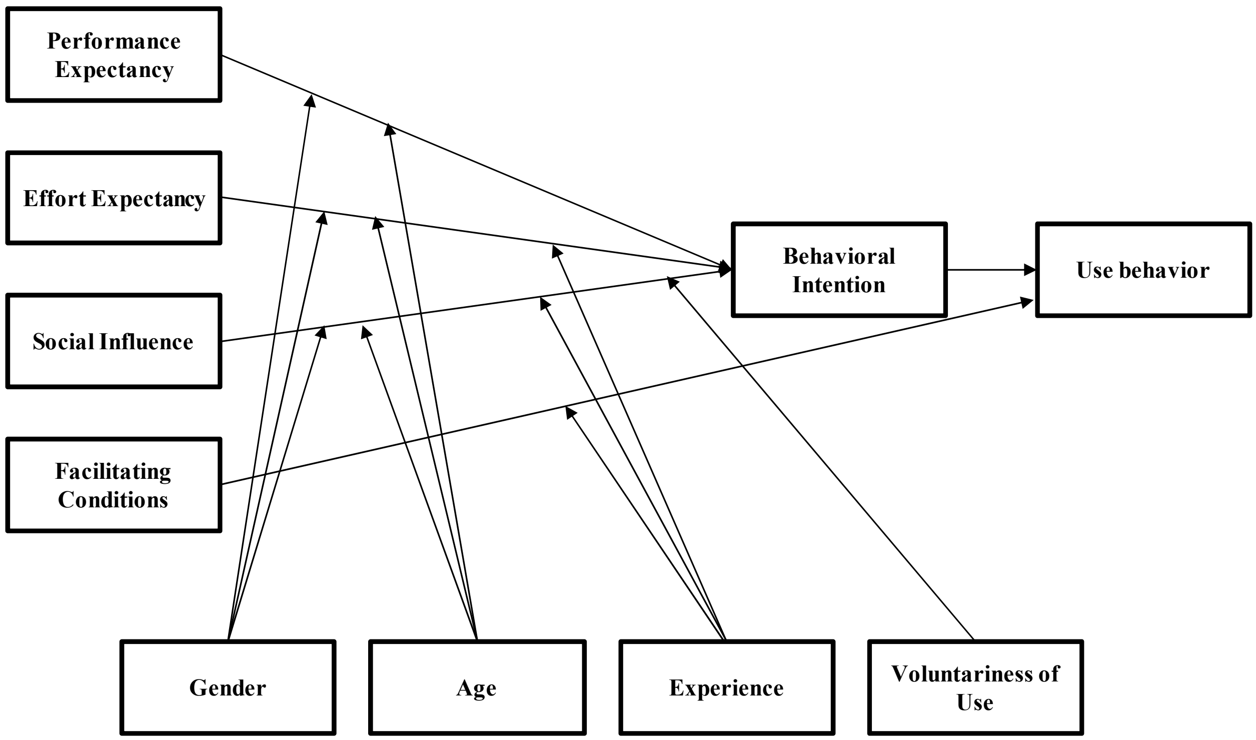


Figure 15: Schematic presentation of Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003, p. 447)

Similar to TAM, since its introduction, UTAUT turned to be a fairly popular theoretical choice in technology acceptance studies and has been through a course of various replications and extensions. In their meta-analysis of UTAUT studies, Dwivedi et al. (2011) identified 870 studies that cited UTAUT, of which 450 used UTAUT constructs (fully or partially) in their empirical studies.

However, alike many other technology acceptance models, UTAUT was developed for organizational and non-consumer context. As a result many studies tried to extend its applicability to the consumer context (Venkatesh et al., 2012). In this perspective, UTAUT, in its original or modified version has been utilized in studies of different technologies in consumer context e.g. acceptance of mobile devices/services (Carlsson et al., 2006; Park et al., 2007; Shin, 2009; Wu et al., 2008), mobile banking (Luo et al., 2010; Zhou et al., 2010), Internet banking. (Abu-Shanab and Pearson, 2009), web based learning (Sumak et al., 2010; van Schaik, 2009), e-government services (Hung et al., 2007; Loo et al., 2009; van Dijk et al., 2008; Wang and Shih, 2009), digital television (Sapio et al., 2010) and online auctions (C.-M. Chiu et al., 2010).

Yet, reviewing UTAUT applications reveals that only a subset of its constructs has been used in consumer context; furthermore, the ever increasing number of consumer technology devices and services makes the consumer technologies an extremely lucrative industry and therefore understanding their acceptance a very important topic. Thus Venkatesh et al. (2012) affirmed the need "*for a systematic investigation and theorizing of the salient factors that would apply to a consumer technology use context*" (p. 158). Accordingly, he introduced the new version of UTAUT labeled as UTAUT2. As shown in Figure 16, the new model is exclusively tailored to consumer context by

- *identifying three key constructs from prior research on both general adoption and use of technologies, and consumer adaption and use of technologies namely hedonic motivation, price value, and habit.*
- *altering some of existing relationships of the original conceptualization of UTAUT that is dropping voluntariness.*
- *introducing new relationships that are relationships between habit and use behavior, price value, hedonic motivation, as well as habit and behavioral intention, including new moderator relationships (age , gender, and experience) for the new constructs and a moderator effect of experience on behavior intention and use (Venkatesh et al., 2012, p. 158).*

Venkatesh et al. (2012) empirically tested the new model by conducting a two-stage online survey of mobile Internet consumers. The results show that the variance explained in behavioral intention and use behavior in UTAUT2 in comparison to UTAUT significantly increased in consumer context, behavioral intention from 56% (UTAUT) to 74% (UTAUT2) and use behavior from 40% (UTAUT) to 52% (UTAUT2). The results of UTAUT2 in consumer context were comparable to the ones of UTAUT in organizational context which confirms the importance of having tailored constructs and models in consumer context.

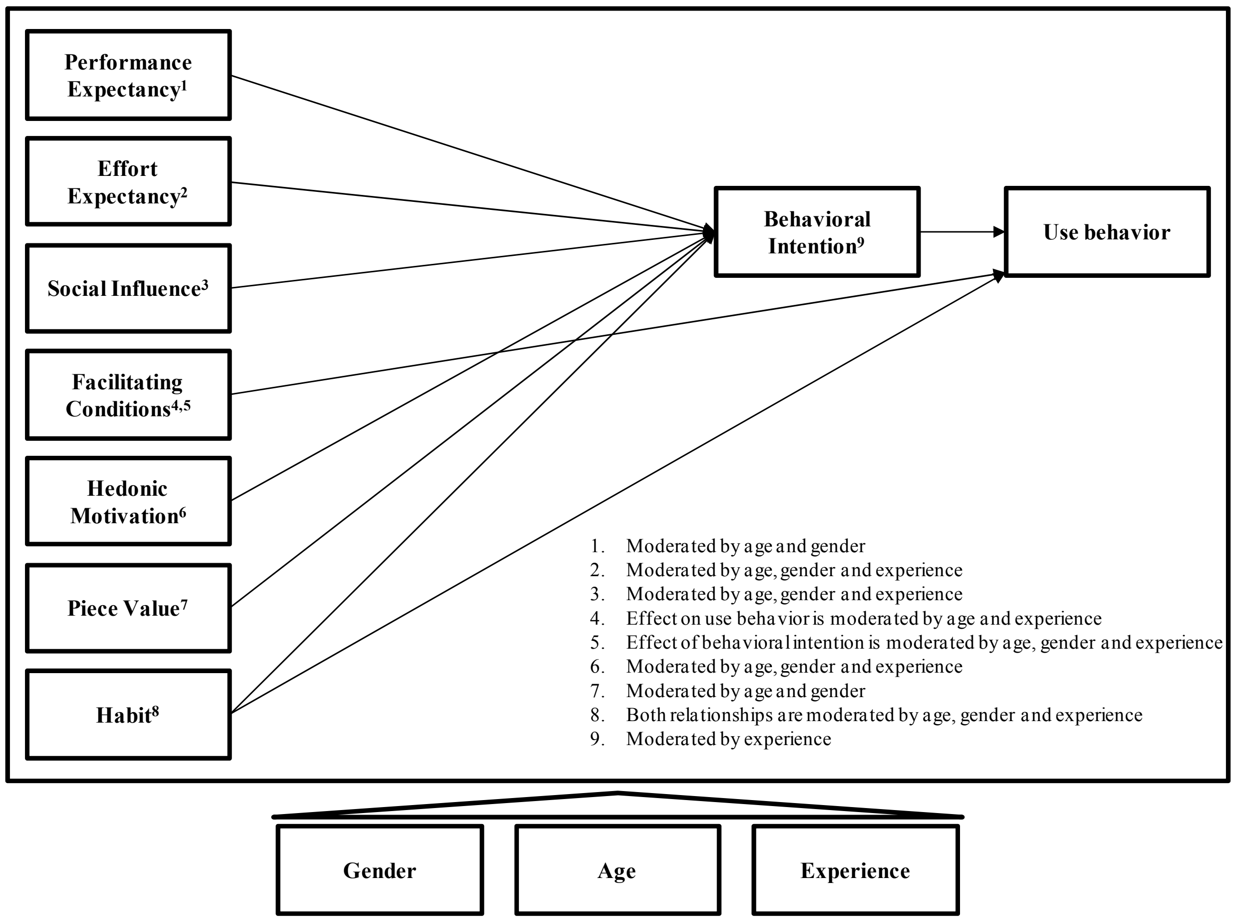


Figure 16: Schematic presentation of UTAUT2 – an extension of UTAUT (Venkatesh et al., 2012, p. 160)

3.1.3 Technology Acceptance Research on Ubiquitous Computing-based Information Services in Brick and Mortar Retail

The ongoing research on acceptance of ubiquitous computing in general (see section 2.1.1) and its in-store applications in particular "*has not yet established a well-accepted set of determinants*" (Hoffmann et al., 2011). Since such applications are still in an early stage of development, it is not surprising that reviewing the literature, only few empirical studies on acceptance of in-store ubiquitous computing based information services exist. In addition, some of the few existing studies are qualitative or exploratory and lacking the modeling and analysis of complex causal relationships. Table 9 lists the existing studies in the field, summarizing their study purposes, research methods as well as key findings. This table is the result of an extensive literature review to locate all of the existing studies which address the acceptance of ubiquitous computing based technologies in traditional retail context.

Table 9: Studies on acceptance of in-store ubiquitous computing-based information services

Author/s (year)	Research purpose	Base model	Extra Factors	End construct/s	Sample size and method	Key findings
(Koller and Königsecker, 2012)	User acceptance of kiosk decision support systems by customers in apparel stores	n/a	n/a	n/a	N:15 Qualitative study Three focus groups of regular apparel shoppers	Usefulness (gathering the information in selected items quickly and easily, receiving up-to-date data, sufficient terminals available to avoid queues) as well as ease of use (easy to use the touch screen) were emerged as essential factors for the acceptance of an information kiosk system.
(Kowatsch and Maass, 2010)	User acceptance of mobile recommender system for in-store product information acquisition	TAM	• Intention to prefer • Intention to purchase	• Intention to use • Intention to prefer • Intention to purchase	N: 47 Paper based survey after a lab experiment Analysis method: PLS-SEM	• Perceived usefulness had a positive significant effect on intention to use. • Perceived ease of use has no significant effect on intention to use. • Perceived ease of use and perceived usefulness had a positive direct relationship with intention to prefer a mobile recommender agent-enabled store and intention to purchase after using the mobile recommender agent.
(Kurkovsky and Harihar, 2006)	User acceptance of mobile recommender system for in-store information acquisition	TAM	n/a	Intention to use	N:34 Paper based survey after visiting a test store	• Ease of use and usefulness had a direct positive influence on intention to use.

Author/s (year)	Research purpose	Base model	Extra Factors	End construct/s	Sample size and method	Key findings
(Kwon et al., 2007)	User acceptance of mobile shopping assistance	TAM	Individual characteristics as antecedents of TAM constructs: • self-efficacy • personal innovativeness • perceived sensitivity	Behavioral intention to use	N: 206 scenario based online survey Analysis method: CB-SEM	• TAM relationships were supported. • Personal innovativeness and self-efficacy had a positive significant effect on PEU. • Personal innovativeness and self-efficacy had no significant effect on PU.
(Lee et al., 2011)	User acceptance of self-service technologies (SSTs) in retail setting (Multimedia information kiosks)	TAM	• Enjoyment • Consumer involvement • Attitude towards using • Service quality	Actual system use	N: 441 Analysis method: CB-SEM	• Ease of use, usefulness, and enjoyment significantly influenced attitude toward using SSTs. • Attitude toward using SSTs had a positive significant impact on intention to use SSTs. • Superior service quality could increase the level of behavioral intention.
(Maass and Kowatsch, 2008)	User acceptance of dynamic product information on mobile devices (DPI)	A Subset of TAM	Relative advantage (of dynamic product information to static one)	Intention to use	N:37 Paper based survey after a lab experiment	Both perceived relative advantage and perceived ease of use were significantly correlated with the intention to use DPI.

Author/s (year)	Research purpose	Base model	Extra Factors	End construct/s	Sample size and method	Key findings
(Müller-Seitz et al., 2009)	User acceptance of RFID based intelligent racks, RFID checkouts, and customer complaint handling	TAM	• Security concerns • Attitude toward novel technologies	Actual system use	N: 206 Customers of two large electronic retail markets Analysis method: multidimensional linear regression model	• The perceived usefulness had the biggest impact on the acceptance of the RFID technologies. • The perceived ease of use had rather a minor influence on customer acceptance of RFID technology. • Security concerns regarding the protection of data privacy were also influential, though the impact was comparatively smaller than that of the other constructs.
(Pantano and Servidio, 2012)	User perception of technology-enabled stores (smart boards)	n/a	• Ease of use • enjoyment	• Consumer satisfaction • Store perception	N: 150 CB-SEM	• Enjoyment turned to be the most powerful predictor of satisfaction and store perception. • The direct positive relationships of ease of use toward perception and satisfaction were supported.
(Rothensee, 2010)	User acceptance of u-Commerce (various store-based ubiquitous computing applications in supermarket environment)	TAM	• Pleasure • Dominance • Trust • Technical competence	Intention to use	N: 306 Paper based survey after a film that described various ubiquitous computing applications in the supermarket of future Analysis method: PLS-SEM	• Usefulness and pleasure strongly influenced intention to use. • Technical competence had a significant influence on perceived ease of use. • Perceived ease of use didn’t have a significant influence on intention to use. • Trust plays a minor role in shaping acceptance. • Dominance plays no role in acceptance.

Author/s (year)	Research purpose	Base model	Extra Factors	End construct/s	Sample size and method	Key findings
(Roussos et al., 2003)	User perception of ubiquitous computing based appliances in retail environment (a supermarket scenario)	n/a	n/a	n/a	N: 60 An exploratory study Paper based survey after a lab experiment	• The majority (49 out of 60) of participants regarded ubiquitous retail as a useful addition to current supermarket shopping options and found the system user friendly and easy to use. • A significant number of participants stated that they would trust the system to do their shopping. • The majority of participants (54 out of 60) expressed their willingness to use the ubiquitous computing based appliances when they become available. • The majority (53 out of 60) of participants stated that they found the experience of shopping in a ubiquitous retail enjoyable with more than half considering it as an exciting activity.
(Spreer and Kallweit, 2014)	Intention to reuse a store owned pad for information search	A subset of TAM	• Perceived enjoyment • Intention to reuse	Intention to reuse	N: 100 Paper based survey from customers of a book store Analysis method: Regression analysis	• Perceived enjoyment had the biggest impact on the intention to reuse. • Perceived usefulness had a positive influence on intention to reuse. • Perceived ease of use had no significant effect on intention to reuse. • The perceived ease of use has rather a minor influence on the intention to reuse.
(Weijters et al., 2007)	User acceptance of self-service technologies in retail setting (self-scanner devices in groceries)	TAM	• Perceived fun • Reliability • Attitude toward using	Actual system use	N: 497 Paper based survey from customers of a grocery store Analysis method: CB-SEM	• Perceived usefulness demonstrated the highest explanatory power on attitude. • Perceived ease of use and fun had a significant positive relationship toward attitude. • The perceived reliability has rather a minor influence on attitude. • User attitudes toward SST positively and significantly affected the actual use.

Author/s (year)	Research purpose	Base model	Extra Factors	End construct/s	Sample size and method	Key findings
(Yang, 2010)	User acceptance of in-store mobile shopping services	UTAUT	• Attitude toward using • Utilitarian performance expectancy • Hedonic performance expectancy	Behavioral intention	N: 400 Analysis method: CB-SEM	• Hedonic performance expectancy had a positive and significant influence on attitude. • The effect of hedonic performance expectancy on attitude was stronger than the effect of utilitarian performance expectancy on attitude. • The effect of effort expectancy on attitude toward using was insignificant. • Social influence and facilitating conditions had a positive and significant effect on behavioral intention. • Attitude had a positive significant influence on behavioral intention of mobile shopping services.

Reviewing the models used in existing studies (see Table 9) unveils that most of the current studies are based on the original TAM model; there is only one study which applies the original UTAUT as its base model. Attempting to better explain the individuals' incentives to use the technology, most of the studies extended the base models by incorporating one or more factors. These additional variables can be categorized in five groups, namely (see Table 9):

- affective factors (e.g. enjoyment, pleasure, hedonic performance expectancy),
- consumers' personal traits (e.g. self-efficacy, dominance, personal innovativeness, technical competence)
- security beliefs (e.g. security concerns, trust)
- consequences of acceptance (e.g. intention to reuse, intention to prefer, intention to purchase)
- service characteristic (e.g. service quality)

Examining the results of the studies listed in Table 9 in regard to two main TAM constructs (Perceived usefulness and ease of use), it can be concluded that perceived usefulness has a significant positive impact on whether in-store ubiquitous computing based information services will be accepted by customers. However, the results for perceived ease of use have been contradictory; although in the majority of studies the relationship of perceived ease of use toward intention to use is supported, four studies could not find any significant relationship (Kowatsch and Maass, 2010; Müller-Seitz et al., 2009; Rothensee, 2010; Spreer and Kallweit, 2014).

Moreover, all of the studies which included affective factors in their models found a direct significant and positive relationship of affective variables toward study's end construct (e.g. intention to use and attitude toward using). Interestingly Spreer and Kallweit (2014) found that perceived enjoyment had the biggest impact on the intention to reuse a store owned pad system for information search and Yang (2010) found that hedonic performance expectancy is a more significant determinant of attitude toward using in-store mobile shopping services than utilitarian performance expectancy.

Regarding security and privacy beliefs, however the general research on acceptance of ubiquitous computing applications has pointed out the importance of these beliefs (Hoffmann et al., 2011), based on the results of the current studies in the area of in-store applications, it can be concluded that security beliefs play a very minor role in shaping the acceptance (Müller-Seitz et al., 2009; Rothensee, 2010). Furthermore, Resatsch et al. (2008) did a prototype based focus group study to understand the needs and expectation of the customers regarding the in-store ubiquitous computing based information services, their results show that privacy was of no concern for the customers.

The results from previous studies are valuable for the acceptance research of in-store ubiquitous computing technologies and undeniably important for the current study. However, existing limitations in these studies restrain comprehensiveness and thus applicability to accurately predict acceptance of any in-store ubiquitous computing based service. The main limitations can be classified into two groups, namely research purpose and base model:

- Research purpose: concerning the study purpose, all of the current studies have taken a rather focused approach. That is focusing either on a single technology (Kowatsch and Maass, 2010; Maass and Kowatsch, 2008; Müller-Seitz et al., 2009; Yang, 2010) or a specific retail context as groceries or apparel stores (Koller and Königsecker, 2012; Rothensee, 2010; Weijters et al., 2007). In fact, this approach limits the generalizability of the findings for all in-store ubiquitous computing based information services. As a matter of fact, none of the studies could offer a generic model to explore user acceptance determinants of both store owned devices and mobile applications on the consumers' smart phones. For example, Koller and Königsecker (2012) exclusively explored the user acceptance of in-store kiosk decision support systems and call for future research addressing the acceptance of mobile applications in general, and in comparison to in-store kiosk solutions.
- Base model: except one single study which is based on the original UTAUT (Yang, 2010), all of the other studies have chosen TAM as their base model. Though TAM was originally theorized to predict the acceptance of technologies in workplace environment and its explanatory power declines when applied in consumer context (Yousafzai et al., 2007b). Furthermore, TAM only focuses on direct determinants of use overlooking the prior/external factors influencing the formation of ease of use and usefulness beliefs and consequently how they could be influenced to promote increased usage (Yousafzai et al., 2007a). In addition, TAM overlooks the influence of important beliefs as normative and affective beliefs (Benbasat and Barki, 2007). As a response to these limitations, from

current studies, five studies have included affective factors to their models; however, all of them ignored the importance of social factors.

- Especially considering such radical technologies as in-store ubiquitous computing based technologies, individuals may consider the usage of technologies as a social status symbol and intent to use to enhance their image among their friends and family members (Lu et al., 2005; Sarker and Wells, 2003). In addition, the role of social factors has been known to be greater in early phases of adoption of an innovation (Triandis, 1971). As the implementation of in-store ubiquitous computing based information services is still in its early stages and therefore individuals have little or no experience on their use, it is more likely that their intention to use will be influenced by opinions of significant others (Thompson et al., 1994; Venkatesh et al., 2003).

3.2 Mass Media Effects Research

Mass communication is defined as "*any form of communication transmitted through a medium (channel) that simultaneously reaches a large number of people*" (Wimmer and Dominick, 2013, p. 2). Respectively, mass media is defined as "*any communication channel used to simultaneously reach a large number of people, including radio, TV, newspapers, magazines, billboards, films, recordings, books, the Internet, and smart media*" (Wimmer and Dominick, 2013, p. 2).

In modern societies, characterized by specialization and diversity, media are considered as a system in control of important information resources which individuals depend on to fulfill their information needs, thus they may cause cognitive (e.g. changes in belief and value system), effective (e.g. changes in feelings), and behavioral changes (e.g. changes in purchase of products and services and decisions concerning the activation or de-activation of media exposure) in consumers who are regularly exposed to them (Ball-Rokeach and DeFleur, 1976; Ball-Rokeach and Jung, 2009; Grant et al., 1991; Ruiz-Mafe and Sanz-Blas, 2006). Therefore, investigating and understanding the effects that media might have on society and individuals has always been the central focus of the mass communication research (Katz, 2001) and its dominant paradigm (Lang, 2013).

More important for the objectives of this dissertation is the stream of research in mass communication whose focus is on individual level analysis of media effects; the research stream which explores the function of mass media on individuals in terms of determinants of their motivation to use a certain medium and the nature of their relations with a certain medium, to understand the effects that a certain medium can cause on individuals' behaviors. The most established theory which allows such individual level exploration of media relations is the media system dependency theory (Ball-Rokeach and DeFleur, 1976).

For more than four decades, media system dependency theory has provided a solid theoretical base to understand consumers' media use motivations and derived consequences. Since its introduction, it has been applied to unfold the relationships between individuals and different media as television (Grant et al., 1991; Skumanich and Kintsfather, 1998), radio and print media (Loges, 1994; Loges and Ball-Rokeach, 1993) and recently Internet (Jung, 2008; Ruiz-Mafe et al., 2014). The central assumption of this theory is that the influences of media will only be powerful if individuals develop a dependency relation with information resources controlled by media. Ball-Rokeach and DeFleur (1976) define dependency as "*a relationship in which the satisfaction of needs or the attainment of goals by one party is contingent upon the resources of another party*" (P. 6). They argue that the intensity of the media dependency relationship is contingent on the perceived utility of a certain medium to meet goals.

One of the objectives of this dissertation is to investigate the potential role of Internet information use on individuals' intention to use in-store ubiquitous computing based information services. Therefore, in this dissertation, the media dependency theory is selected as theoretical framework to identify the effects that the use of the Internet as an information medium can cause on individuals and hypothesize their influences on cognitive and effective beliefs concerning the use of in-store ubiquitous computing based information services.

Hence, the remainder of this section is dedicated to review of relevant literature on media system dependency theory; starting from the origins, explaining the approach of media dependency theory in individual level as well as arguing its superiority comparing to competing model of uses and gratification. This section will be closed by an exhaustive review of studies on applications of individual media dependency in IS research, particularly in the context of Internet.

3.2.1 Media System Dependency Theory

However, identifying the media effects has been the primary concern of mass communication research; it has been always characterized by great controversy and even conflicting views among theorists and scholars. Specifically, the disagreement about the magnitude of media influences has even shaped the dominant historical narrative of the discipline itself around the polarized notions of significant versus minimal effects (Neuman and Guggenheim, 2011). The progression of the classical media effects literature was typically characterized as a three-stage succession, starting with the prevalence of the magic-bullet theories positing strong media effects followed by a pull in the opposite direction and the adoption of the model of minimal effects and finally the renunciation of the earlier works in favor of the rediscovery of powerful media influences (Lowery and De Fleur, 1983).

Typically attributed to the academic works concerned with propaganda and centralized media control between the world wars, the magic bullet perspective contends the simplistic concept of treating media messages as magic bullets targeted towards passive audience members who lacked independent sources of information. This formulation posits that media effects are direct, unmediated, immediate and uniform (McCombs, 2004; Wicks, 1996). This paradigm was quickly proved to be exaggerated and even mythical after being discarded by empirical findings. Notably, the work of Lazarsfeld et al. (1948) on the effects of political campaigns on voting behavior, introduced the social science methodology of survey research to the mass communication field and provided groundbreaking empirical evidence of the invalidity of the magic bullet effect model. These findings opened the door for more consolidating research against the idea of massive influences leading to the limited effects conceptualization. This approach assumes that media influences are constrained by individual and social differences meaning that only few people could be affected by certain media and this only in distinct situations (Lowery and De Fleur, 1983).

The accumulating failure to prove more than small effects despite the glaring impact of media on modern society split scholars between those who attempted to find compelling influences and those confirming the notion of limited effects. While the latter mostly focused on adding more specificity by investigating new variations of distinct groups, social situations, mediums and message types, the former aspired to solve the problem through more theoretical complexity. This controversy within mass communication research pushed the discipline to tackle the matter of media effects each time from different paradigms and perspectives and was a driving force behind its theoretical richness. However, it also resulted in less abstraction within the field and more concerning theoretical dissimilarity and contradiction, while always failing to provide a standout formulation that best explains mass media effects.

The theory of media system dependency comes about from the need for an overarching theory that synthesizes previous paradigms to allow for generalizable knowledge (Ball-Rokeach and DeFleur, 1976). Ball-Rokeach and DeFleur (1976) avoid taking a sterile all or none approach by integrating the previous findings, instead of simply taking sides in a conflicting line of research. Specifically, their theory attempts to explain when and why do media exert power on individuals and society and with what consequences, rather than narrowly seeking to prove whether media do have significant influences or not. In other words, the theory avoids pre-assuming generalizations of powerful or minimal effects and offers another theoretical alternative that focuses on investigating the conditions under which those effects might occur.

The originators of the theory blame the tenacious ambiguity surrounding media effects on "*wrong theoretical conceptualizations to study the wrong questions*" (Ball-Rokeach and DeFleur, 1976, p. 3), suggesting that previous research relied too heavily on psychological theory adaptations at the expense of the sociological perspective.

Ball-Rokeach and DeFleur (1976) admit that the previous approaches allow for engaging more specificity and simplicity regarding the investigated variables and are convenient to demonstrate how media effects can vary among individuals. However they argue that the bias in the preceding body of research towards micro level analysis tackling specific units of individuals, in specific situations, eventually favored conceptualizations that overlook the englobing social context within which the media and its audience exist and how these components among other social structures interact together; such interactions happen on a massive scale and their engendered effects can take a long time to manifest due to the sophisticated nature of these relationships. Hence those influences are very difficult to capture through commonly conducted laboratory stimulus-response experiments that focus on individuals' short term reactions to media messages, in specific situational conditions.

Therefore, Ball-Rokeach and DeFleur (1976) regard the preceding formulations as unable to grasp the full complexity of the mass communication processes, and recommend involving more sociological theory elaborations instead of solely approaching the issue of media effects from the individual (micro) level of analysis. Particularly, they suggest that works of Durkheim (1933), Marx (1961), and Mead (1934) can provide a better framework to investigate media influences, one which considers that neither media nor its audience exist in a vacuum, rather they are pivotal components of a social system.

On one hand, according to the symbolic interaction paradigm of Mead (1934), people base their actions upon meanings and these meanings are shaped through the encountered social perspectives. People would employ the information resources around them to create meanings in order to act properly. On the other hand, in societies of complex structure, characterized by specialization and diversity, interpersonal communication becomes restricted and ineffective in providing people with the information they need to make sense of their environment. Thus individuals become unaware of the guiding norms of the larger society and therefore incapable of constructing their social realities, which creates a state of ambiguity (Durkheim, 1933). Hence media as a system in control of important information resources imposes itself as a way to fill the void engendered by the social structure of modern society. This leads systematically to the creation of interdependent relations between media and other social components, which can be in terms of cooperation or conflict and change, both at the level of individuals, groups or large scale social systems (Ball-Rokeach, 1998).

The most direct influencing theory on the MSD formulation is Emerson's (Emerson, 1964, 1962) power-dependency theory (Ball-Rokeach, 1998). This theory considers that dependence is the flip side of power, meaning that power lies not in the relative superiority of resources' control but rather in the extent to which those resources produce dependence. Power is thus above all relational and based on the dynamics between resources and dependences, which can be sustained or lost. In a similar manner, Ball-Rokeach tries to explain why media effects can be powerful in some occasions and weak in others. In fact, Emerson's perspective inspired her to formulate MSD as a media power theory built around a central conceptualization: the media dependency relation.

Ball-Rokeach and DeFleur (1976) define dependency as "*a relationship in which the satisfaction of needs or the attainment of goals by one party is contingent upon the resources of another party*" (P. 6). Therefore, the power of mass media is contingent upon the dependency of individuals on the media controlled information resources. Media control three types of resources: information gathering or creating, information processing and information dissemination. However, the dependency relationship can be in both ways, meaning that the media system itself may depend upon the resources controlled by others. Media power in relation to other social systems is determined by the distribution of resources and dependencies between them.

Unlike Emerson, Ball-Rokeach and DeFleur (1976) follow the social ecology approach of considering the micro or individual media system relations in the context of the higher influence of the macro level systems relations that is relations between media systems and other systems as economic and political systems. They argue that although interdependencies flow in both directions from small to large units and vice versa, the macro-level of influence is stronger. In fact, the structural dependency relations between media and other social systems (e.g. economic and political system) are set to characterize the dependency relations between media on one hand and individuals and interpersonal networks on the other. Ultimately, while the media centrality in shaping personal meaning can be intervened by psychological, sociological differences, it is largely determined by the extent to which macro media system dependency relationships permit media to be pivotal in social knowledge construction.

MSD is hence conceived as an ecological theory that integrates both micro and macro units of analysis through media dependency relations. According to the theory, it is only in the light of the relations between media, audience members and the larger social system, that the complex process of mass communication can be explained. Even further, Ball-Rokeach and DeFleur (1976) propose these relations as a way out from the dilemma of why media influences seems to be sometimes powerful and sometimes not. In other words, the nature of those relations defines the nature and intensity of behavioral, affective and cognitive media effects. As the originators of the theory most clearly posit, "*whatever the particulars of the relationship, it is the relationship that carries the burden of explanation*" (DeFleur and Ball-Rokeach, 1989, p. 303).

3.2.2 Individual Media System Dependency Relations

The micro level of MSD relations also known as individual media system dependency (IMD) relations revolves around the assumption that individuals are contingent upon access to information resources controlled by media in order to attain their personal goals. Unlike prior mass media theories such as uses and gratification theory (Katz et al., 1973) in which individual media use were presented in terms of gratification of needs, MSD presents individual media use in terms of attainment of goals. This conceptualization of the human motivations behind media exposure which favors goals over needs, derives from the theory's "*insistence on keeping the audience member social as well as psychological*" (Ball-Rokeach, 1998, p. 26).

The originators of the theory argue that goals provide a more appropriate conceptualization of the individual motives behind media information consumption. Implying a problem-solving motivation, goals are more responsive than needs to changes and difficulties occurring in the individual's personal and larger social environs. Therefore, considering audience members as goal-oriented individuals, located in a social environment where media controls central information resources, is more compatible with a social ecology conceptualization of macro MSD relations. In other words, attainment of personal goals depends on media information resources and hence IMD relations can be strongly altered by the macro relations media have with other social systems. This approach avoids perceiving IMD relations as a product of merely individual characteristics or overlooking their overarching environmental and structural contexts (Ball-Rokeach, 1998, 1985).

However, IMD relations cannot be narrowed down to personal goals; for instance, dependency on media is rather the contingency relation between these goals and media resources than just a function of individual goals. Thus, by definition, variations in individuals' media system dependency relations do not only occur when goals are altered but ultimately when the perceived utility of media resources to attain these goals changes. Consequently, individuals sharing same hierarchy of goals do not necessarily have the same individual dependency relations with media (Ball-Rokeach, 1998, 1985).

3.2.2.1 Determinants of Individual Media System Dependency Relations

As mentioned, IMD relations are function of goals and perceived utility of media resources. In turn goals and perceived utility are influenced by macro media system dependency relations, social environs, media activity, interpersonal networks and individuals' structural locations (Ball-Rokeach, 1985; Ball-Rokeach and Jung, 2009; Grant et al., 1991). Figure 17 illustrates all influencing factors in construction of individual media system dependency relations.

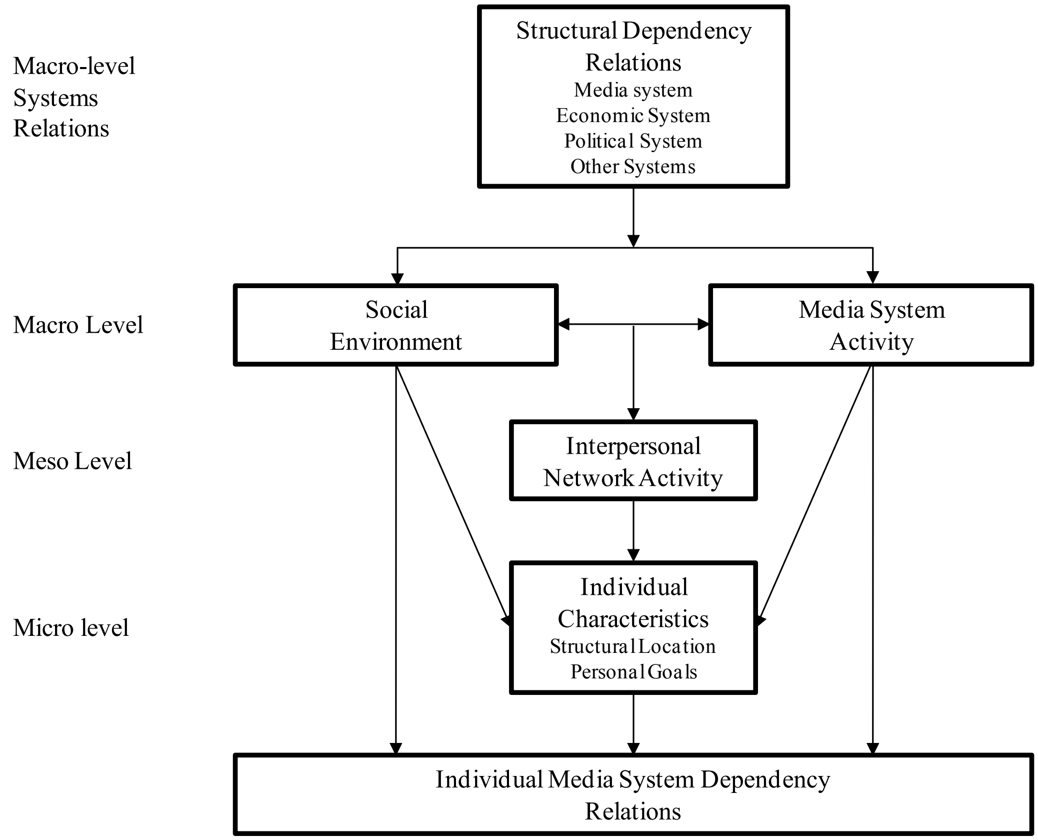


Figure 17: Determinants of individual media system dependency relations (Ball-Rokeach and Jung, 2009, p. 535)

Macro media system dependency relations are central when it comes to determining the nature of micro media dependency relations. Individuals live in societies where media has interdependency relationships with other social systems such as economic and political systems. These relations also known as structural dependencies, define the range and exclusivity of knowledge construction roles that can be attributed to media in the society and thus the potential range of media dependencies that individuals can develop. In other words, the more macro media system dependency relations allow media to provide a larger number of exclusive and central information functions, the more likely that media will have a considerable influence on individuals. Therefore, structural dependencies are the central determinant of individuals' media dependencies. Further, these macro media system dependencies establish a coherent context for examining the other origins of variation in micro dependency relations among the individuals of the same society (Ball-Rokeach, 1998, 1985; Ball-Rokeach and Jung, 2009).

These sources of variations include social environs, meaning any environs that are susceptible to affect personal goals. Ambiguity and threat are two social environ attributes that are expected to alter individual media dependency relationships. In fact, problematic situations, whether accruing on the personal or social level, can cause a state of cognitive and affective discomfort which pushes individuals to employ the accessible information resources around them in order to achieve their goals of coping with and overcoming those chronic conditions. Specifically, when the social environs are undergoing conflict and change and therefore prominent aspects of these environs can be perceived as uninterpretable, unpredictable and/or threatening, individuals' reliance on media is more likely to be intensified.

This leads to another important determinant of individual media dependency relations: media activity. As structural dependencies "*place the media in the position of being an essential link between individuals and their social environs*" (Ball-Rokeach, 1985, p. 501), media can systematically implicate in constructing the perceived ambiguity and threat of individuals' social environs. Therefore, the message focus of the media is assumed to have a considerable effect on micro MSD relations.

Similarly, the message focus of audience members' interpersonal networks can have an impact on their individual media dependency relations through influencing their personal goals. This is because Individuals' goals can change in order to fit better with the social influence of their interpersonal networks.

Lastly, audience members' dependencies on media can also be affected by their structural location within their societies. Individuals' structural location determines their potential resources acquisition and thus can impact their media system dependency relationships, especially through personal goals (Ball-Rokeach, 1985). For example access to alternative media resources, can alter these dependency relationships (Ball-Rokeach, 1998).

3.2.2.2 Typology of Individual Media System Dependency

MSD theory perceives individuals as having three general types of goals, namely understanding, orientation, and play (Ball-Rokeach et al., 1984; Grant et al., 1991). Accordingly individual's motivations to use media information resources is in order to attain these goals (Ball-Rokeach, 1998; DeFleur and Ball-Rokeach, 1989). Therefore, the individual media dependency typology proposed by the theory consists of three dimensions, each of which in turn comprises of a personal and social dimension resulting in six different types of media dependency relations presented in Table 10.

Table 10: Typology of individual media dependency relations

Dimension	Understanding	Orientation	Play
Personal Dimension	Self-understanding	Action orientation	Solitary play
Social Dimension	Social understanding	Interaction orientation	Social play

On one hand, this typology is assumed to encompass all possible individual dependency relations. On the other hand, the occurrence of one type of dependency doesn't necessarily exclude the others, rather individuals can seek to achieve understanding, orientation and play goals at the same time through the same media resources. Additionally, all dependency dimensions are perceived to be equally important for individuals and thus have the potential to produce equally central media dependency relations (Ball-Rokeach, 1985).

Understanding dependency relations occur when audience members are motivated to employ media information resources in order to establish knowledge and meaningful interpretations of themselves and their social environs. While self-understanding dependencies derive from the motivation to acquire the capacity to comprehend one's self and to interpret personal aspects such as one's beliefs and behavior, social understanding dependencies concern contingency on media information resources to make sense of the surrounding world including interpretation of occurring, past or future events, and apprehension of the guiding norms of larger society (Ball-Rokeach, 1985; Ball-Rokeach and Jung, 2009).

Individuals typically employ the understanding they gain in order to act properly and meaningfully. This leads us to another dimension of individual dependency on media: orientation dependency. This media dependency dimension stems from the individual motivation to obtain the necessary decision-making guidance in order to behave correctly, whether on the personal level or with others. Action orientation dependencies revolve around seeking direction and support from media information resources, when it comes to performing behaviors concerning solely individual actions that do not involve interacting with others. Such behaviors can include purchasing items, voting, planning activities, etc. Contrariwise, interaction orientation dependencies are about contingency on media with the objective to figure out how to behave in a manner that provides or maintains effective relationships whether they are personal, professional, communal or other (Ball-Rokeach et al., 1984; Ball-Rokeach and Jung, 2009).

Equally central are play goals. The MSD theory posits that individuals rely on media for play driven by escape and tension release goals labeled as solitary play dependencies. Furthermore, play fulfills important learning, communication, expression and socialization roles that are crucial for both individuals and societies. While solitary play dependencies revolve around the disseminated content and its capability to directly engender relaxation stimulation and/or recreation, social play concerns more the medium's capacity to provoke and facilitate bonding and interaction between individuals through co-participation in play activities rather than the proprieties of the content itself (Ball-Rokeach et al., 1984; Ball-Rokeach and Jung, 2009).

This typology of individual media dependency relations is assumed to be valid for examining whole audiences as well as particular social groups and individuals. Moreover, the typology can be applicable to depict audience members' dependencies on media systems in general, singular mediums, and even dependency relations with specific media products.

3.2.3 Individual Media System Dependency in Information System Research

As Wimmer and Dominick (2013) state in their recently updated definition of mass media, the Internet undeniably has become an instance of mass media. As of the 30th of November 2015, there are more than three billion Internet users in the world that is around 46% of the world's population ("World Internet Users Statistics and 2015 World Population Stats," 2015). In Germany, meanwhile about 80% of population use the Internet from which 63% use it daily (Frees and Koch, 2015). Thus the Internet can be used as a communication channel to simultaneously reach a large number of people and therefore an instance of mass media.

Adopting the theoretical concepts from reference disciplines to explore and understand the conceptually analogous processes in IS contexts has been a long tradition in IS research. For example adoption of TRA from social psychology (Davis, 1989) (see section 3.1.2) and Uses and Gratification theory from mass communication (Larose et al., 2001; Shao, 2009; Smock et al., 2011; Stafford et al., 2004) to information technology acceptance and use. In the same manner, since the Internet has reached the mass audience, media system dependency theory has attracted IS researchers, as it offers a robust foundation to explore individuals' motivations to use and effects of using the mass media.

MSD theory has been employed as a theoretical framework to investigate the Internet dependency relations on both the macro and micro ecological levels of analysis. From the macro level perspective, several studies have inquired the determinants and outcomes of the structural interdependencies between the Internet and other social systems (Groshek, 2012, 2011, 2009; Zhang, 2006); or tried to explain the variations and the effects of the individual Internet dependency relations by examining the macro-origins of dependencies, such as structural dependencies as well as ambiguous and/or threatening social environs (Jung, 2012; Kim et al., 2004; Lyu, 2012; Tai and Sun, 2007).

For past two decades, Internet has been a key driver to economic growth and its role is expanding. For example, in Germany, the Internet economy accounts for 65 billion Euros only in 2014 and for the period of 2015-2019, this amount is expected to grow 12% annually till reaching 114 billion Euros in 2019 (Riegel et al., 2015). Based on MSD theory, the above mentioned figures translate to interdependencies of economic system and the Internet, macro/structural dependencies. Therefore it can be argued that the structural dependency relations have been already formed for this medium (see Figure 17). Thus there is a dependency between the Internet as a specific mass medium and the economic system that is merchandisers of goods and services are dependent on Internet information resources to disseminate consumption-stimulating messages. Based on MSD theory as the structural dependency relations are formed, there must be also individual media dependency instances. Therefore, IS researchers have started to adopt the MSD theory focusing on the micro determinants and outcomes of individual dependency on the Internet, meaning the personal and situational origins as well as the cognitive, affective, and behavioral effects of dependency relations.

As the micro level of analysis is more relevant to the purpose of this dissertation, to examine the applicability of MSD theory in investigating the micro determinants and outcomes of individual Internet relations, an exhaustive literature review was carried out. Articles using the theory, however without employing it as the focal point of the study were discarded. Additionally, studies focusing on political or news information were considered to be outside the scope of this review. An extensive search of peer reviewed journals through relevant academic publishing databases (e.g., Elsevier Science Direct, Emerald Insight, and Google Scholar) provided 10 academic articles.

The first study which used the theoretical perspective of media system dependency in the context of the Internet focusing on micro level of analysis was the work of Patwardhan and Yang (2003) which introduced the Internet dependency relations as a predictor of online consumer activities. Based on the MSD theory they defined Internet dependency relations (IDR) as *the extent to which people depend on the Internet* [information] *to meet their social and personal goals* (P. 57). They postulated that the intensity of the general Internet dependency relations positively influences Internet users' online shopping (including product information search, alternative evaluation activities, and product purchase) experience. The empirical results can show that IDR as a summed intensity (considering all goal dimensions) had a significant positive effect on online shopping. In addition, they have tested the relationship between the action orientation goal dimensions and the online shopping activity; action orientation was found to be an even stronger predictor of online shopping experience.

Since the introduction of IDR by Patwardhan and Yang (2003), nine other studies adopted the theoretical perspective of the media system dependency to examine the determinants and outcomes of using the Internet or Internet based applications. The key findings of these studies have been presented in Table 11 (Ben Abdelaziz, 2015). The findings of the recent adoptions of micro level MSD theory in the Internet context demonstrate its applicability to the context.

Table 11: Studies using MSD theory in the context of Internet – micro determinants and outcomes of the Internet dependency

Author/s (year)	Subject of Dependency	Theme	Key Findings
(Bigne-Alcaniz et al., 2008)	Online Shopping	Dependency Determinants & Outcomes	Innovativeness and online information dependency predicted future online shopping intention. Perceived usefulness mediated the positive effect of perceived ease of use on online shopping information.
(Jung, 2008)	Internet	Internet Connectedness Determinants	Scope and intensity of Internet-related goals, social and technological environments significantly influenced individuals' Internet Connectedness.
(Jung et al., 2012)	Internet	Internet Connectedness Dimensions & Outcomes; Internet goals Dimensions & Outcomes	The goals that adolescents had for going online affected the types of activities they engage online and also their use of other media.

Author/s (year)	Subject of Dependency	Theme	Key Findings
(Men and Tsai, 2013)	Social Media	Dependency Outcomes	Social media dependency, parasocial interaction and community identification predicted public engagement with corporate social network sites (SNSs).
(Patwardhan and Yang, 2003)	Internet	Dependency Outcomes	Internet Dependency Relations (IDR) predicted online consumer activities. IDR predicted online shopping activities and online news reading, however not online chatting. Action orientation, solitary play and social understanding, predicted online shopping, online chatting, and online news reading, respectively.
(Riffe et al., 2008)	Internet for In-Depth Information	Dependency Determinants & Outcomes	Dependent respondents valued Internet over other sources of in-depth information sources. Individual background variables predicted dependency.
(Ruiz-Mafe and Sanz-Blas, 2006)	Internet	Dependency Determinants & Outcomes	Age, education, Internet affinity, exposure and experience predicted Internet dependency. Internet dependency predicted willingness to purchase online, with searching for information to take decisions as the most relevant factor.
(Ruiz-Mafe et al., 2014)	Facebook Fan Pages	Dependency Outcomes	A significant positive influence of perceived usefulness, attitude, trust and dependency on loyalty in fan pages, and an indirect influence of perceived ease of use mediated by perceived usefulness and attitude.
(Sun et al., 2008)	Internet	Dependency Determinants	Motivation was a more relevant predictor of Internet dependency than demographics. Cognitive and affective involvement mediated the relationship between motivation and dependency.
(Wang and Yang, 2008)	Online Shopping	Dependency Determinants	Respondents with high levels of harmonious passion and obsessive passion significantly had higher online shopping dependency. Compulsive buyers are more dependent on online shopping than the other.

4 Exploring Consumers' Acceptance of Ubiquitous Information Services in Brick and Mortar Retail – Conceptual Model and Research Hypothesis

The purpose of this chapter is to develop a comprehensive and theoretically found conceptual framework which can explain the antecedents and consequences of the user acceptance of in-store ubiquitous computing-based information services. To do so, first the approach taken for the development of the conceptual framework is discussed. The guidelines for the context-specific theorizing in information system research from W. Hong et al. (2013) is used to build an acceptance model for the context of in-store ubiquitous computing-based systems.

Pursuant to these guidelines, first the most appropriate base model is selected to guide the contextualization process. In the next step the rationale to incorporate the Internet dependency relations into the technology acceptance model is discussed. Furthermore, the constructed model is augmented by germane user-specific variables derived from the customer research literature. Research hypotheses derived from the conceptual framework will be then empirically tested in chapter 5.

4.1 Developing a Context-Specific Theory in Information Systems Research

However, the generalizability in different contexts and settings is one of the important attributes of a theory, in the information system research, there has been a widely recognized need for the context-specific theory development (Chiasson and Davidson, 2005; Orlikowski and Iacono, 2001; Rosemann and Vessey, 2008; Venkatesh et al., 2007). In fact the first theory in the field, TAM, is the result of the contextualizing social psychology theories into the context of information systems (see section 3.1.2). Taking the context into consideration while developing theories leads to the emergence of richer and more practically relevant theories (Bamberger, 2008; Bliese and Jex, 2002; W. Hong et al., 2013). In this regard, W. Hong et al. (2013) note that "*one way to develop richer theories that provide actionable advice is to take the context into greater consideration to generate insights about the phenomena associated with the information technologies, individuals, and organizations*" (p. 2).

Johns (2006) defines the notion of the context as "*situational opportunities and constraints that affect the occurrence and meaning of (…) behavior as well as functional relationships between variables*" (p. 386). Synthesizing various definitions from the literature, Whetten (2009) defines context effects as "*the set of factors surrounding a phenomenon that exert some direct or indirect influence on it-also characterized as explanatory factors associated with higher levels of analysis than those expressly under investigation*" (p. 31). Thus the context can be a significant driver of the cognition, beliefs, and the behavior or the moderator of relations among them (Bamberger, 2008).

Based on the above-mentioned definitions, in the field of technology acceptance research, contextual factors which may have direct or indirect impacts on the technology usage behavior can be classified into three categories, namely characteristics of technology-based services, characteristics of technology artifacts and situational characteristics:

- Characteristics of technology-based services: dimensions of users' perceptions may vary dependent on the characteristics of technology-based services, also in some literature referred to as the system type (W. Hong et al., 2013). For example, in the case of an online banking system, users' perceptions of systems' security may have a direct influence on its acceptance (Pikkarainen et al., 2004). However, considering the perceived security for the acceptance of an e-book reader device is not as justifiable by the type of the system. Similarly incorporating perceived enjoyment as a direct influencing factor of acceptance of a gaming application can be justified by hedonic nature of the system, however this cannot be the case while analyzing a pure performance based system as a project management system. Regarding the system type factors, W. Hong et al. (2013) note that "*although these factors are context specific, they are not directly connected to system characteristics but serve to capture high-level user perceptions about a system*" (p. 6).
- Characteristics of technology artifacts: characteristics of technology artifacts are one of the context factors which are considered while context-specific theorizing (W. Hong et al., 2013). In fact characteristics of technology artifacts vary contingent on the type of technology itself as well as its usage contexts; thus no one usage conceptualization can fit all technologies (Lee and Baskerville, 2003; Orlikowski and Iacono, 2001). For example, whereas download speed may influence users' perceptions of usefulness of a wireless

Internet, the usefulness perception of an e-book reader may be influenced by the quality of its screen. Technology characteristics are used either as indirect or moderating factors on the usage of a technology. For example Lu et al. (2005) incorporated technology complexity as the antecedent factor of usefulness and ease of use while developing a TAM based model for the acceptance of wireless Internet. Similarly Pikkarainen et al. (2004) added quality of the Internet connection in their acceptance model of online banking.

- Situational characteristics: situational characteristics by themselves are divided into two categories, namely usage context (e.g. organizational vs. personal) and characteristics of users (e.g. experienced users vs. inexperienced) (Hevner et al., 2004). In this regard, Boiney (1998) notes that "*the same technology will not provide the same results with each group and in each setting*" (p. 343). Likewise Gopal and Prasad (2000) emphasize that technology cannot be studied outside its social context and refer to inconsistent results in the information systems research as potential consequence of overlooking the value of social context. UTAUT2 is a prominent example of the contextualization of the original UTAUT (designed for organizational context) into the personal usage context; the model also incorporates user characteristics e.g. age and gender as moderators of its core relationships (see section 3.1.2.3).

Not surprisingly, as a subfield of information systems research, the need for development of context-specific theories is also recognized for the acceptance of ubiquitous computing technologies. In this regard, Yoon and Kim (2007) note that "*ubiquitous computing technology is seen as an emerging new information technology with such potency that it has changed the way we view IT. Although perceived ease of use and perceived usefulness constructs have been considered important in determining the individuals' acceptance and use of IT in the last few decades, factors contributing to the acceptance of a new IT are likely to vary according to the technological characteristics, the target users, and the context*" (p. 102). Furthermore, a recent literature review article of technology acceptance studies calls for the development of context specific models for the state of the art technologies as ubiquitous computing (Chen et al., 2011).

After all, the ultimate goal of the implementation of ubiquitous computing technologies in brick and mortar stores is to entice customers to shop in these stores, not to merely be a generic information system. However, review of the literature on the acceptance of in-store ubiquitous computing systems (see section 3.1.3) shows that the majority of existing studies used TAM for their analysis; but TAM doesn't capture the context characteristics that are specific to ubiquitous computing settings.

In line with the objectives of this dissertation and as a response to the need for the development of context-specific models in the field of ubiquitous computing technologies, the remaining of this chapter is dedicated to the development of a context-specific conceptual framework for the acceptance of in-store ubiquitous computing-based information services. To do so, the guidelines for the context-specific theorizing in information system research from W. Hong et al. (2013) are used.

Examining the prior research and classifying the existing approaches, W. Hong et al. (2013) recently introduced a framework as well as a set of guidelines for context-specific theorizing in information systems research. They have divided the contextual theory development practice into two general approaches, namely single-context theory contextualization and cross-context theory replication. Whereas the latter approach is concerned with the validation of the generalizability of theories in different contexts, the former approach is concerned with the refinement of general theories based on the specific contexts being studied. The main objective of this dissertation is developing a theoretically found model for the user acceptance of in-store ubiquitous computing-based information services; thus theory development in this dissertation is an instance of the single-context theory contextualization approach and not cross-context theory replication. Figure 18 is an illustration of contextual theorizing approaches in which the approaches taken by this study are highlighted. The rationales for selecting the level 2a and 2b (see Figure 18) are discussed in corresponding sections (see section 4.4).

In line with the objectives of this dissertation, different levels of contextualization are needed for the development of the conceptual framework, namely service characteristics, technology characteristics, and user characteristics. Thus, based on the proposed framework and guidelines of W. Hong et al. (2013), while single context theoretical contextualization, the following stages shall be taken

- selecting a general theory as a base model,

- contextualizing the general theory into the context of in-store ubiquitous computing-based information services (general characteristics of technology-based services),
- finer contextualizing of the context-specific general model to user characteristics in general and characteristics of users induced by expanding penetration of the Internet in particular (user characteristics),
- and finer contextualizing of the context-specific general model to service and technology characteristics.

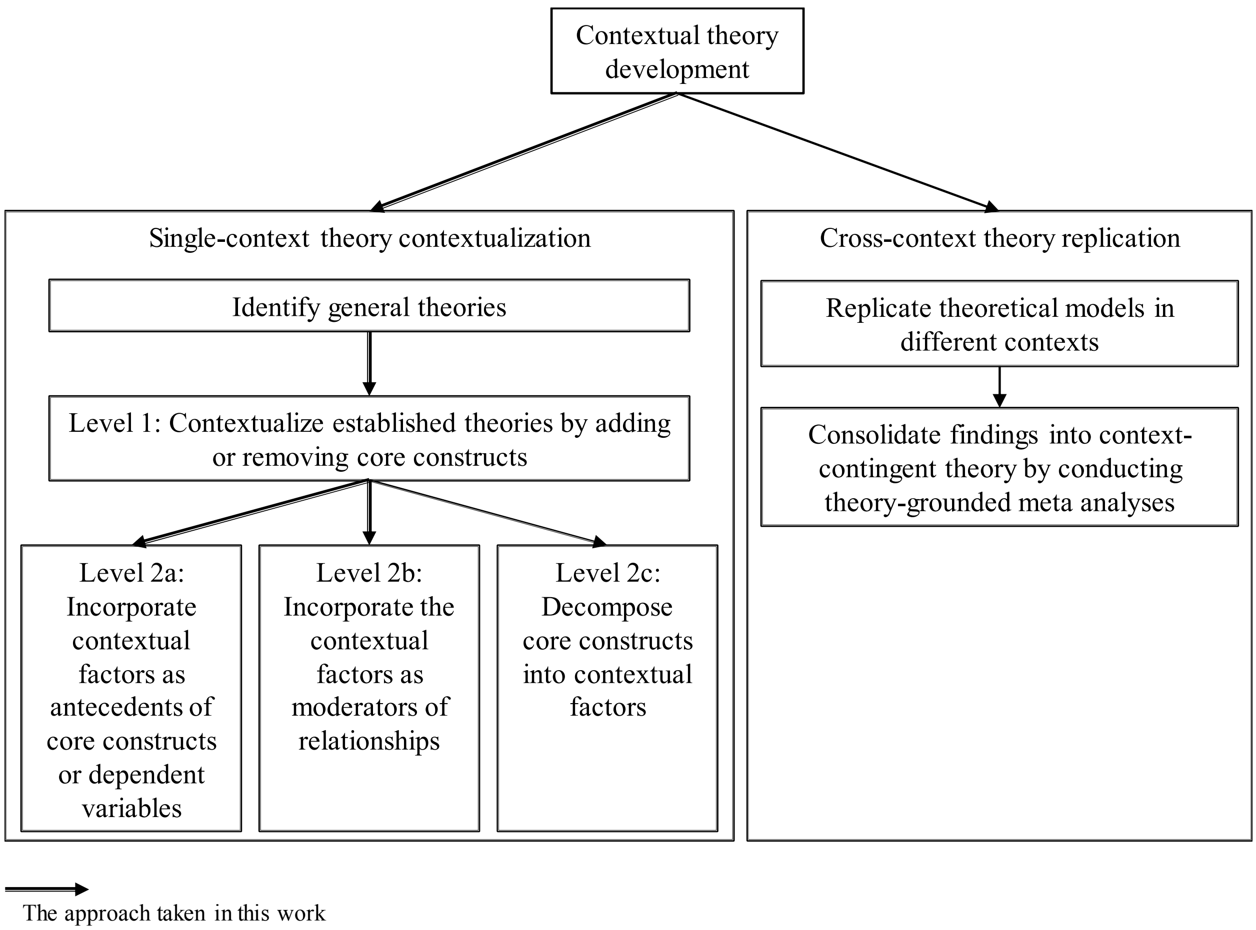


Figure 18: Approaches for incorporating the context into theorizing (W. Hong et al., 2013, p. 5)

Figure 19 is an illustration of above mentioned stages accompanied with the corresponding steps from W. Hong et al.’s (2013) context-specific theorizing guidelines in information systems research adapted to the objectives of this dissertation.

Few steps have been already taken in in prior chapters to build the foundation for the theory development; the remaining steps will be taken in the course of this chapter till complete development of an acceptance model for in-store ubiquitous computing-based information systems.

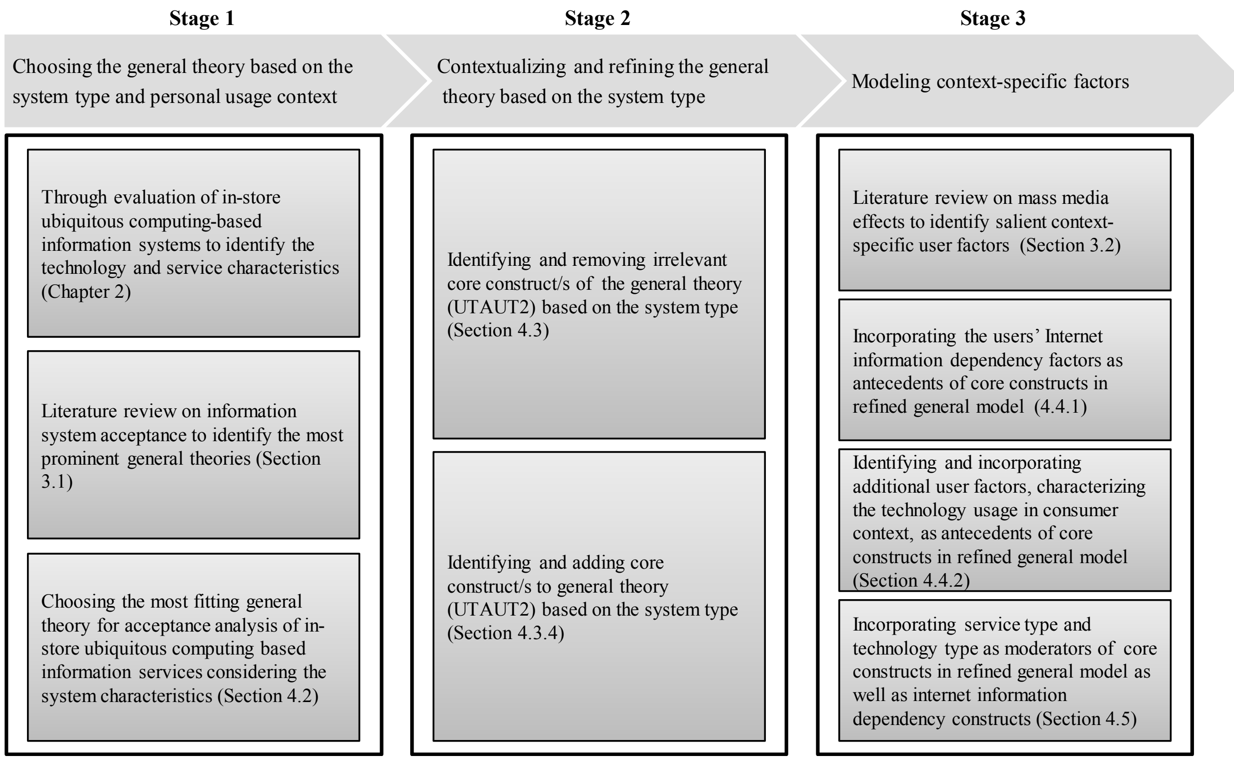


Figure 19: The procedure of contextual theory development in this dissertation based on the guidelines of (W. Hong et al., 2013)

4.2 Choice of the Base Model

The first step in the W. Hong et al's (2013) guidelines is to select a base model. That is selecting a general theory which functions as a core component of the context-specific model to regulate the contextualization process (W. Hong et al., 2013).

Considering the objectives of this dissertation and building on the preceding literature analysis on technology acceptance research in general and acceptance of in-store ubiquitous computing information services in particular, this dissertation sets out to apply UTAUT2 as its base model. For the purpose of this study UTAUT2 is a better fit over traditional technology acceptance models like TAM for several reasons:

- An established theory: as W. Hong et al. (2013) note, "*although both established and emerging theories may be adopted to guide the development of context-specific models,* *researchers adopting an established theory, (…), will encounter fewer challenges, particularly in terms of explaining the relevance of theory to the contexts*" (p. 8). UTAUT2 is developed by leading researchers in the field of technology acceptance. It is based on the UTAUT which was created by synthesizing eight dominant and established models in the field. In addition, UTAUT2 is one of the few acceptance models which is already contextualized into the context of consumer technologies. However established, because of its newness in comparison to the older models, the number of replication studies for its generalizability are yet limited. In this regard Venkatesh et al. (2012) call for replication studies on different technology contexts. Thus by choosing UTAUT2 as a base model, this dissertation not only follows the W. Hong et al.'s (2013) guidelines but also it reflects to the Venkatesh et al.'s (2012) call concerning the future research in UTAUT2.

- A powerful model in the context of the consumer technology use: the original UTAUT is empirically proven to vigorously outperform all of the eight previous models and their extensions in terms of the explained variance (see section 3.1.2.3) (Venkatesh et al., 2003). The empirical results of UTAUT2 in the consumer context are comparable to the ones of UTAUT in organizational context (see section 3.1.2.3) (Venkatesh et al., 2012). Last but not least, while extending the boundaries of classical TAM-based models, UTAUT2 retains a parsimonious structure (Venkatesh et al., 2003).
- Incorporating both affective and social factors: affective factors as hedonic motivation as well as social factors as social influence are known to have a significant role in the acceptance of technologies in the retail setting (Rintamäki et al., 2006a; Yim et al., 2013). Therefore, it is expected that these factors will play an important role in the acceptance of in-store ubiquitous computing systems. In their paper on the context-specific theorizing in information system research, W. Hong et al. (2013) note that "*the choice of a general adoption model should adequately capture the key core constructs relevant to the context. For example, in contexts where social influence is of great importance in understanding user acceptance, general models that capture this aspect, such as UTAUT, will be appropriate.*" (p. 8). UTAUT2 is one of the few general technology acceptance models which covers both of these aspects.
- Including moderator effects: last but not least, due the importance of including moderators in acceptance models in terms of avoiding inconsistencies and low explanatory power (Dwivedi

et al., 2011; Sun and Zhang, 2006), UTAUT2 provides a good framework to enquire the moderating effects that are in the scope of the current dissertation (i.e., age and gender).

4.3 Contextualizing UTAUT2 into In-Store Ubiquitous Computing-based Information Services

After selecting the base model, the next step in developing a contextual theory is contextualizing and refining the base model (see Level1 in Figure 18 and Stage 2 in Figure 19). The contextualizing and refinement of the base model is done by removing the context irrelevant core constructs and adding the minimal set of core constructs which are relevant to the context (W. Hong et al., 2013).

The original UTAUT2 posits that seven distinct factors determine individuals' behavior intention to use a technology: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. In turn, behavior intention to use a technology determines the technology use behavior (see Section 3.1.2.3 and Figure 16). Table 12 lists the determinants of the behavior intention as well as their definitions. In addition, UTAUT2 posits that age, gender, and experience moderate the core relationships (see Section 3.1.2.3 and Figure 16).

Table 12: Direct determinates of individuals' intention to use a technology in original UTAUT2 (Venkatesh et al., 2012, 2003)

Direct determinants of behavior intention	Definition
Performance Expectancy	The degree to which using a technology will provide benefits to consumers in performing certain activities
Effort expectancy	The degree of ease associated with consumers' use of the system
Social influence	The degree to which a consumer perceives that important others believe he or she should use the new system.
Facilitating conditions	The degree to which an individual believes that an organizational; and technical infrastructure exists to support use of the system
Hedonic motivation	Fun or pleasure derived from using a technology
Price value	Consumers cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them
Habit	The extent to which people tend to perform behaviors automatically because of learning

In line with the contextualizing and refining the base model, UTAUT2, into in-store ubiquitous computing-based information services, the following modifications are made to the original model:

- The construct "use behavior" is excluded from the model. Since diffusing in-store ubiquitous computing-based information services is yet in its embryonic stage and users rarely had the opportunity to use such services, the actual use behavior cannot be observed. Therefore in this work, user acceptance is examined by behavior intention rather than actual use, considering that behavior intention is a good predictor of the actual use behavior (Ajzen, 2011; Ajzen and Fishbein, 1980; Yousafzai et al., 2007a).
- For the same reason, behavior intention determinant of "habit" and the moderator factor of "experience" are eliminated; both of these factors are related to the previous use of the same technology which in regard to in-store ubiquitous computing-based information services is most probably not the case.
- Behavior intention determinants "facilitating condition" and "price value" are as well excluded. Facilitating condition captures the impact of supportive infrastructure which is not applicable in the current research setting. Correspondingly, price value is only applicable when the use of a technology device or service is associated with monetary costs for users. However, in-store ubiquitous computing information services are considered as free of cost applications to improve the customer experience in store.
- A new construct of "intention to prefer" has been added as a consequence of behavior intention to use the technology. In the context of this dissertation, intention to prefer is defined as the degree to which users will prefer a retail store which offers in-store ubiquitous computing-based services. As mentioned in section 4.1, the key objective for the development of contextual theories is to provide more practically relevant advices. Incorporating the notion of intention to prefer into the UTAUT2 is in line with this objective; the answer to the question if the intention to use ubiquitous computing information services influences user preference of stores which offer such technologies has crucial practical meanings for retailers, specially while deciding about implementing such technologies. The rationale for the relationship between behavioral intention and intention to prefer will be discussed in more detail in this section while developing the

corresponding hypothesis. The primary theoretical model for this dissertation resulted from the above-mentioned adjustments in the original UTAUT2 is depicted in Figure 20.

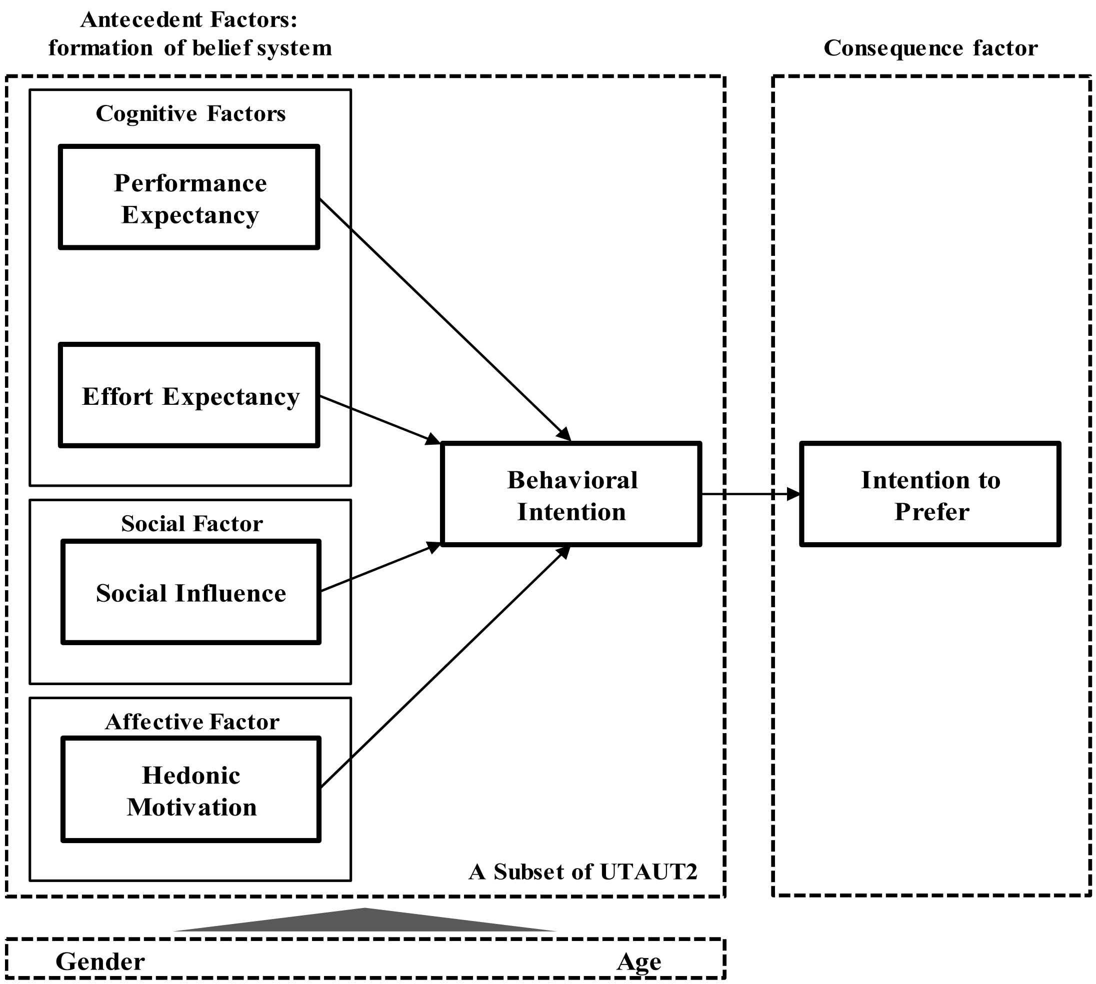


Figure 20: The primary research model – adjusted UTAUT2 to the context of ubiquitous computing information services

Four factors (beliefs) are expected to play a direct role in customers' use intention of ubiquitous computing-based information services. Thus, the belief system pertains to cognitive, affective and social beliefs. Below, the rationale for the relevance of each relationship to the present context will be discussed followed by the formulation of each theoretical relationship as a research hypothesis.

4.3.1 Cognitive Factors

According to TRA and TPB, while an individual is deciding about performing a certain behavior, her behavioral beliefs are formed by both cognitive and affective evaluation of the consequences of that behavior (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 2010) (see sections 3.1.1.1 and 3.1.2.2). The cognitive dimension of behavioral beliefs in TAM has been translated into two cognitive factors of perceived usefulness and ease of use (see section 3.1.2). As a result, in technology acceptance studies, the cognitive and utilitarian perspective which is the answer to the question of "how useful a system is?" has been included since the introduction of original TAM. UTAUT and UTAUT2 as well encompass this cognitive dimension by incorporating performance expectancy and effort expectancy factors as direct determinants of the behavioral intention.

4.3.1.1 Performance Expectancy

Davis justifies the direct relationship between the perceived usefulness and behavioral intention in TAM by referring to the assumption that people build their intention to use an information system by cognitive assessment of potential performance improvements (Bagozzi, 1982). That is if a system improves the performance of a user, regardless of her attitude toward the using, the resulting benefits can drive the use intention (Konana and Balasubramanian, 2005).

In line with the development of a unified theory (UTAUT), Venkatesh et al. (2003) empirically compared the eight prominent models in the technology acceptance research (see section 3.1.2.3). They have identified five conceptually similar constructs in these models which covered the notion of performance expectancy. The performance expectancy factor within each individual model turned out to be the strongest predictor of the intention. However, it is important to note that Venkatesh et al. (2012) empirically tested the UTAUT2 in consumer context and found that hedonic motivation is more important driver of behavioral intention than performance expectancy.

In retail setting, performance expectancy stands for the utilitarian aspect of the act of shopping which asserts that while shopping, customers are concerned with conducting the act of buying in a timely and efficient manner (Childers et al., 2001). Thus, in the context of in-store ubiquitous computing-based information systems, performance expectancy captures customers' beliefs regarding the performance value of the technology; that is if using the technology will improve their shopping performance. Indeed, augmenting retail stores by ubiquitous computing systems increases the quality of service in terms of speed and convenience (Zhu et al., 2013). That is easier access to a large amount of information on products and improved response time to consumers' requests. These systems are designed to target the service quality blockages as unprepared frontline employee, low speed in consumers' requests and long queues resulting from limited human resources (Pantano and Migliarese, 2014). These utilitarian benefits, if perceived by consumers, are likely to drive customers to use the system.

The reviewed studies on the acceptance of in-store ubiquitous computing-based technologies (see Table 9) which included the notion of performance expectancy could find a direct and positive relationship between the performance expectancy and use intention (Kowatsch and Maass, 2010; Kwon et al., 2007; Lee et al., 2011; Müller-Seitz et al., 2009; Rothensee, 2010; Weijters et al., 2007). Consistent with the results of Venkatesh et al. (2003), in two studies performance expectancy was the most significant predictor of behavioral intention (Müller-Seitz et al., 2009; Weijters et al., 2007). Müller-Seitz et al. (2009) studied the acceptance of RFID based services in the retail setting, e.g. intelligent racks providing product information; their empirical analysis showed that perceived usefulness had the biggest impact on the acceptance of the in-store RFID-based services. Likewise Weijters et al. (2007) conducted an empirical study on the acceptance of mobile self-scanners in the grocery retail setting; similarly they concluded that perceived usefulness demonstrated the highest explanatory power on intention.

Consistent with UTAUT2 and the evidence from the previous literature, it is expected that users focus on potential performance benefits when facing the choice of using in-store ubiquitous computing-based information services. Thus, the hypothesis to be tested is:

H2: Performance expectancy has a significant positive effect on behavioral intention to use in-store ubiquitous computing-based information services.

4.3.1.2 Effort Expectancy

Along with the performance expectancy, since the introduction of TAM, effort expectancy has been considered as one the most important drivers of intention to use technologies. Capturing the same notion as TAM's perceived ease of use, the effect of effort expectancy on behavioral intention has accumulated significant support in the literature (Dabholkar and Bagozzi, 2002; Davis et al., 1989; Kwon et al., 2007; Venkatesh et al., 2003).

Consistent with the previous research, in consumer context, Venkatesh et al. (2012) found that effort expectancy had a significant effect on behavioral intention. The rationale behind this relationship is that customers' perceptions concerning the degree of ease to learn and operate a system positively influence their intention to use a particular technology.

However, all of the prominent technology acceptance models as TAM, UTAUT and UTAUT2 consider effort expectancy as a direct and important determinant of the behavioral intention, empirical evidence on its role in the acceptance of in-store ubiquitous computing information services is mixed. Although in the majority of studies the relationship of effort expectancy toward behavioral intention is supported (see Table 9, P. 65), four studies could not find any significant relationship (Kowatsch and Maass, 2010; Müller-Seitz et al., 2009; Rothensee, 2010; Spreer and Kallweit, 2014).

Given the strong theoretical basis and consistent with UTAUT2 as well as the evidence from the previous literature, it is expected that the ease with which consumers can operate the in-store ubiquitous computing-based information systems will positively affect their intention to use such systems. Thus, the hypothesis to be tested is:

H1: Effort expectancy has a significant positive effect on behavioral intention to use in-store ubiquitous computing-based information services.

However, it is important to note that because of the inconsistent results of the previous empirical research this hypothesis is stated with caution.

4.3.2 Social Factor: Social Influence

The importance of the social context on the formation of individual's perceptions regarding a certain object has been emphasized by social psychologists (Robertson, 1989; Triandis, 1979). Hence the notion of the subjective norm was included in TRA and TPB as one of the major determinants of intention (see section 3.1.1.1). According to TRA, subjective norm is a function of normative beliefs (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 2010) and defined as "*an individual's perception* (belief) *that most people who are important to her think she should perform a particular behavior*" (Fishbein and Ajzen, 2010, p. 131). This is a measure of the perceived social pressure to perform or to refrain from a behavior in question. It results from aggregation of the perceived expectations of reference persons or groups regarding a certain behavior and willingness to behave according to these expectations. So the beliefs concerning what different people or groups consider correct or incorrect behavior as well as beliefs about what important others are actually doing are the informational foundation to form an individual's subjective norm (Fishbein and Ajzen, 2010).

Although TAM overlooked the effect of the subjective norm in its original form, its originator, Davis, later noted that it is essential to consider the subjective norm in technology acceptance studies (Davis, 1986; Davis et al., 1989). As a result several scholars incorporated the notion of subjective norm in technology acceptance models (see section 3.1.2.1) using different labels as social influence and image (see section 3.1.2.1 and Table 7). However utilizing different labels, these factors stand for the notion that "*the individual's behavior is influenced by the way in which they believe others will view them as a result of having used the technology*" (Venkatesh et al., 2003, p. 451). In line with development of original UTAUT, Venkatesh et al. (2003) empirically compared three different factors of subjective norm, social factors, and image and found that all of these factors behave similarly. The notion of subjective norm is included under the term of social influence in both original UTAUT and UTAUT2 (see section 3.1.2.3). Several studies could empirically support the direct positive influence of social factors on usage intention of various technologies in different contexts (e.g. Hsu and Lin, 2008; Hsu and Lu, 2004; Mun et al., 2006; Venkatesh et al., 2012, 2003)

As discussed in section 3.1.2.3, the impact of social influence on the individual behavior is through three mechanisms: compliance, identification and internalization. Compliance refers to a perceived social pressure by an individual while deciding to use or not to use a technology; that is when a person adopts a behavior not because she wants it herself but with an incentive of receiving a reward. Therefore the consideration of compliance effects can be only logical when those important others have the ability to reward the favored behavior or punish in the case of refusing to perform the favored behavior (Venkatesh et al., 2003; Warshaw, 1980). That means only in mandatory settings which is often the case in organizational settings (Hartwick and Barki, 1994). Therefore, for the current analysis which is absolutely in a voluntary setting, compliance is not expected to have an impact on behavioral intention.

Social influence in voluntary contexts functions through identification and internalization mechanisms (Venkatesh et al., 2003). This means that an individual may intent to use a technology believing that the important others, e.g. family members and friends, will do the same and simply rely upon their opinions and/or in response to the potential social status gains among them. Therefore, in the context of this dissertation, social influence is defined as the degree to which an individual believes that members of her family and friends think she should use in-store ubiquitous computing-based information services.

In retail context, social factors are known to have a significant role in the acceptance of technologies (Rintamäki et al., 2006a; Yim et al., 2013). The effect of social influence is expected to be more salient in the case of new and advanced technologies as in-store ubiquitous computing-based information services (López-Nicolás et al., 2008; Lu et al., 2005; Sarker and Wells, 2003). Individuals may consider the usage of novel technologies as a social status symbol and intent to use to enhance their image among their friends and family members and identify themselves as a member of the more innovative user group (Lu et al., 2005; Sarker and Wells, 2003). In addition when a penetration of a certain technology is not substantial, users may perceive it as rare and fashionable and intend to use it to enhance their social status (López-Nicolás et al., 2008).

Furthermore, the role of social influence has been known to be greater in the early phases of adoption of an innovation (Triandis, 1971). In the early phases of adoption, individuals often have little or no experience on the use of the particular technology and thus on its potential utilitarian advantages, hence the expectations and opinions of family and friends concerning a newly introduced technology may have a greater influence on behavioral intention to adopt that technology (Teo and Pok, 2003; Thompson et al., 1994; Venkatesh et al., 2003).

Consistent with UTAUT2 and considering the characteristics of in-store ubiquitous computing-based information services, that is being new and advanced technology which is in early phases of implementation and adoption, it is expected that the perceived expectations and opinions of family and friends regarding the use of in-store ubiquitous computing based information technologies will positively affect consumers' intention to use of such technologies. Thus, the hypothesis to be tested is:

H3: Social influence has significant positive effect on behavioral intention to use in-store ubiquitous computing-based information services.

4.3.3 Affective Factor: Hedonic Motivation

According to TRA and TPB, while an individual is deciding about performing a certain behavior, her behavioral beliefs are formed by both cognitive and affective evaluation of the consequences of that behavior (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 2010) (see sections 3.1.1.1 and 3.1.2.2). However TRA and TPB advocated the influence of affective belief on behavioral intention, it was excluded from TAM; the argument was that, within organizational context, individuals form their behavioral intention toward use of a certain technology when they believe that the use of the system will increase their performance "*over and above whatever positive or negative feelings may be evoked toward the behavior per se*" (Davis et al., 1989, p. 986). As extensively discussed in section 3.1.2.2, this assumption doesn't hold for all contexts and technologies; as a result, a new stream of research has been evolved seeking to integrate affective factors into the technology acceptance models. In line with this stream of research, various labels are created to capture the affective response of individuals associated with system use (see Table 8). In fact, many empirical studies could show the important role of affective factors in determining the technology acceptance and use (Brown and Venkatesh, 2005; Chang and Cheung, 2001; Koufaris, 2002; Moon and Kim, 2001; Thong et al., 2006; Venkatesh et al., 2012).

In consumer context, the importance of the affective reactions in consumer decision making has been long recognized (Batra and Ahtola, 1990; Childers et al., 2001; Holbrook and Hirschman, 1982); overall the motivation of customers to buy or use a product or service is divided into two, cognitive and affective dimensions (McGuire, 1976). That is customers assess their shopping experience not only based on the perceived utilitarian value of the attained products and services but also on the enjoyment they perceive from the use of the products and services (Babin et al., 1994). In consumer research literature, these dimensions are usually referred as hedonic and utilitarian components of consumer choice (Batra and Ahtola, 1990). Therefore, while tailoring the UTAUT to consumer context, Venkatesh et al. (2012) added the factor of hedonic motivation to capture the affective dimension of technology use (see section 3.1.2.3). Consistent with the prior research on IT adoption in non-organizational contexts (Van der Heijden, 2004), the empirical results of UTAUT2 showed that hedonic motivation is a more important determinant of consumers' behavioral intentions to use a technology than performance expectancy.

Furthermore, Donovan and Rossiter (1982) could confirm the environmental psychology model of Mehrabian and Russell (1974) in retail settings; in their model, Mehrabian and Russell (1974) postulate that individuals react to environments with approach or avoidance behaviors. Approach versus avoidance is defined as a desire and willingness to physically stay, to explore the environment, to communicate with others in the environment, and the degree of enhancement of task performances. Mehrabian and Russell (1974) suggest that perceived pleasure in an environment is one of the important causal variables for an approach behavior. That is a perceived pleasurable environment will be approached, whereas the unpleasurable one will be avoided. Creation of a positive emotional experience in the retail environment can generate enjoyment and pleasure (Hoffman and Novak, 2009). Referring back to the Mehrabian and Russell's (1974) theory, pleasure in turn results in customer satisfaction and thus approach behavior. That is the retail environment generating a pleasurable experience is more likely to be approached by consumers.

All of these assumptions are also valid for technologies in retail environment; affective factors as hedonic motivation are known to have a significant role in the acceptance of technologies in retail setting (Rintamäki et al., 2006a; Yim et al., 2013). For the case of ubiquitous computing systems, their introduction into stores is expected to improve the stores appearance in terms of style, layout, and atmosphere making them more appealing and pleasurable (Grewal et al., 2013; Pantano and Naccarato, 2010). In this regard, Pantano and Naccarato (2010) compare new in-store technologies with videogames: "*consumers can play with products as in a videogame, due to the high level of interactivity of technologies*" (p. 203). Therefore, it is expected that such technologies provide more hedonic value to customers and thus trigger an approach behavior that is a tendency to use the technology.

Moreover, regarding the technology acceptance studies on in-store ubiquitous computing-based information services, all of the studies which included affective factors in their models found a direct significant and positive relationship of affective variables toward study's end construct (e.g. intention to use and attitude toward using) (see section 3.1.3). Interestingly Spreer and Kallweit (2014) found that perceived enjoyment has the strongest impact on the intention to reuse a store owned pad system for information search and Yang (2010) found that hedonic performance expectancy is a more important determinant of the attitude toward using in-store mobile shopping services than utilitarian performance expectancy.

Given the strong theoretical basis and consistent with UTAUT2 as well as the evidence from the previous literature, it is expected that the perceived hedonic value of in-store ubiquitous computing-based information services will be positively associated with the customers' intention to use them. Thus, the hypothesis to be tested is:

H4: Hedonic motivation has a significant positive effect on behavior intention to use in-store ubiquitous computing-based information services.

4.3.4 Intention to Prefer

Customer acquisition and retention is one of the key objectives of every retail store. In the literature, it is argued that through improved point of sale and enhanced customer services, ubiquitous computing enabled stores would be able to reach-out to new customers and retain the existing ones (e.g. Bitner et al., 2002; Grewal et al., 2013; Pantano and Migliarese, 2014; Pantano and Naccarato, 2010, 2010; Poncin and Ben Mimoun, 2014). In other words, it is assumed that customers will prefer the ubiquitous computing enabled stores to the other stores. Undeniably gaining relative advantage over other stores is the primary motive for implementing ubiquitous computing technologies. Therefore, from retailers' perspective not only it is important to understand if and how consumers will accept the in-store ubiquitous computing information services but also whether the acceptance rate of in-store ubiquitous computing services positively influences consumers' preferences of the stores offering such services.

To answer this question, a new construct of "intention to prefer" is added to the base model. In the context of this dissertation, intention to prefer is defined as the degree to which users will prefer a retail store which offers in-store ubiquitous computing-based information services. Similar to the actual use, actual preference cannot be observed for futuristic systems. However, according to TRA, behavioral intention is a strong predictor of actual behavior; therefore, in this work, intention to prefer is considered to be a satisfactory approximation of customer's actual preference.

Based on UTAUT2, the usage of in-store ubiquitous computing-based information services is predicted by consumers' behavioral intentions. However, a customer can only use the ubiquitous computing based technologies for searching and evaluating information in a brick and mortar store when they are available in the store. Therefore, when a customer intends to use in-store ubiquitous computing information services, it is more likely that she would also prefer a ubiquitous computing enabled store.

Building on a similar rationale, Kowatsch et al. (2011) hypothesized a direct positive relationship between intention to use digital product reviews using mobile devices in retail stores and intention to prefer review-enabled stores. Conducting an empirical study, they could confirm that intention to use strongly influences the intention to prefer.

Based on the above-mentioned rationale as well as the evidence from the previous literature, it is expected that the intention to use in-store ubiquitous computing-based information services will positively affect the customers' intentions to prefer ubiquitous computing enabled stores. Thus, the hypothesis to be tested is:

H5: Behavior intention to use in-store ubiquitous computing based information services has a significant positive effect on customers' preference of stores offering such services

4.3.5 Moderators

As mentioned in section 4.2, considering the purpose of the current research, one of advantages of UTAUT2 to other technology acceptance models is incorporating the moderator factors of age and gender. Characteristics of users are one of the situational characteristics which are often used for the context-specific theorizing (see section 4.1). Among user characteristics, age and gender are the most prominent factors with a strong impact on individual's perceptions (Nosek et al., 2002) particularly perceptions of technology (Morris et al., 2005; Venkatesh et al., 2003; Venkatesh and Morris, 2000).

Extensive research in the consumer behavior shows that the needs and wishes of customers are diverse based on their socio-demographic background. Thus in marketing and customer research literature socio-demographic factors specifically age and gender are often used for customers' segmentation (Anselmsson, 2006; Bhatnagar and Ghose, 2004; Royne Stafford, 1996). Through a comprehensive literature review in technology acceptance studies, Niehaves and Plattfaut (2014) state that age and gender are the most used socio-demographic variables in the field, respectively used in 87% and 95% of the reviewed studies followed by income and education used in only 9% and 10% of the studies. Therefore researchers in the field of technology acceptance argue that incorporating these factors as moderators of beliefs, intention relationships in the research model will increase the contribution of results in the marketing strategy development (Dabholkar and Bagozzi, 2002; Nysveen et al., 2005). The knowledge about existence of age and gender induced decision making differences in the acceptance of in-store ubiquitous computing-based information services can be used by retailers to design marketing strategies to appropriately address the customers and when necessary to intervene their decisions and consequently increase the probability that the service will be continually used. Therefore, studying the role that age and gender may have on the relationships between beliefs and behavioral intention is crucial for the context of this dissertation.

4.3.5.1 Age

There is an overwhelming evidence in the literature that younger people have a more positive attitude towards new information technologies (Bigne-Alcaniz et al., 2005; Burton-Jones and Hubona, 2006; Mulhern, 1997; Rai et al., 2013). Regarding in-store ubiquitous computing information services, it is also expected that younger customers will be more favorably disposed towards using emerging shopping schemas (Kourouthanassis and Giaglis, 2005). In his exploratory research, Burke (2002) found that younger adults are considerably more interested to use every instant of ubiquitous computing-based information services (e.g. handhelds, palm computers and interactive kiosks) for both searching product information and evaluating the alternatives in the shop. Therefore, it can be assumed that younger adults perceive new technologies differently than older ones and hence the magnitude of acceptance determinants of in-store ubiquitous computing information services may differ from younger to older age groups.

Explicitly concerning the effect of age on belief-intention relationships, previous empirical research shows that whereas performance expectancy is a stronger determinant of younger users' intentions, the effect of effort expectancy on intention is more salient for older users (Morris and Venkatesh, 2000; Venkatesh et al., 2003). Respectively while the effect of social influence increases with age (Morris and Venkatesh, 2000; Venkatesh et al., 2003), the importance of hedonic aspect of a novel technology use decreases (Ha et al., 2007; Venkatesh et al., 2012).

In information system research literature, these age-induced decision making differences are often explained by theoretical foundation of behavior changes (changing needs, a mellowing process) (Gibson and Klein, 1970) and cognitive changes (decline in cognitive and memory capabilities) (Law et al., 1998; Minton and Schneider, 1985; Welford, 1980) occurring through aging process (Morris et al., 2005; Morris and Venkatesh, 2000; Venkatesh et al., 2012, 2003).

Older people tend to consider the extrinsic, performance-based rewards less valuable than younger ones and therefore consider the usefulness of a technology not as important reason to use the technology as younger users may do (Venkatesh et al., 2003). Respectively because of declining cognitive and memory capabilities, older people have more difficulty in processing complex stimuli (e.g. a new technology artifact) and focusing on the task itself, therefore the ease with which they can work with a system is more salient reason to use a technology than for younger users (Venkatesh et al., 2003). Based on a comprehensive literature review on age differences in consumers' information processing, Phillips and Sternthal (1977) concluded that social influenceability increases with age, suggesting that when confronted with a new stimulus, older consumers are more likely to base their decisions on peers' opinion than their younger counterparts. Hence, the expectations and opinions of family and friends concerning a newly introduced technology may have a greater influence on older consumers' use intentions than younger ones. On the other hand younger individuals are more receptive to new ideas and keen to try novel technologies (Lee et al., 2010) and make their use decisions independently (Midgley and Dowling, 1978). Such novelty seeking contributes to hedonic motivation to use a novel technology (Holbrook and Hirschman, 1982). Therefore, younger consumers are more likely to be driven by hedonic motivation to use a new technology than the older ones.

Consistent with UTAUT2 and based on the above-mentioned rationale as well as the evidence from the previous literature, it is expected that age has a moderating effect on the relationships between behavior intention to use in-store ubiquitous computing based information services and its antecedents. Thus, the hypotheses to be tested are:

H1.1: The influence of effort expectancy on behavior intention will be moderated by age such that the effect will be stronger for older people than younger people

H2.1: The influence of performance expectancy on behavior intention will be moderated by age such that the effect will be stronger for younger people than older people

H3.1: The influence of social influence on behavior intention will be moderated by age such that the effect will be stronger for older people than younger people

H4.1: The influence of hedonic motivation on behavior intention will be moderated by age such that the effect will be stronger for younger people than older people

4.3.5.2 Gender

There is a consensus among numerous studies that men have a more positive attitude towards new information technologies (Gefen and Straub, 1997; Parasuraman, 2000; Venkatesh and Morris, 2000). Regarding in-store ubiquitous computing-based information services, Elliott and Hall (2005) assessed gender differences in consumers' propensity to embrace self-service technologies in retailing. They found that men were more eager to make use of new technologies than women. Similarly, in his exploratory research, Burke (2002) found that men were considerably more interested to use every instant of ubiquitous computing based information services (e.g. handhelds, palm computers and interactive kiosks) for both searching product information and evaluating the alternatives in the shop. Therefore, it can be assumed that men perceive new technologies differently than women and hence the impact of acceptance determinants of in-store ubiquitous computing information services may differ for men and women.

Explicitly concerning the effect of gender on belief-intention relationships, the previous empirical research shows that whereas performance expectancy is a stronger determinant of male users' intention, the effect of effort expectancy on intention is more salient for female users (Venkatesh et al., 2003; Venkatesh and Morris, 2000). Respectively while the effect of social influence is stronger for women (Venkatesh et al., 2003; Venkatesh and Morris, 2000), the importance of hedonic aspect of a novel technology use is higher for men (Ha et al., 2007; Venkatesh et al., 2012).

From theoretical point of view, such apparent gender decision making differences are often explained by reinforced culture induced psychological differences rather than biological differences between genders (Bem, 1981; Brosnan, 1998; Brosnan and Davidson, 1996; Lynott and McCandless, 2000). Gender differences in customers' decision making behavior is also acknowledged in marketing literature; for example, it is found that women employ different information processing strategies than men (Meyers-Levy and Maheswaran, 1991). That is women often conduct a more comprehensive information processing while shopping (Cleveland et al., 2003; Laroche et al., 2003, 2000). Furthermore men are mainly derived by utilitarian purchase motivations (Citrin et al., 2003). Therefore while women tend to prefer to concentrate on the act of shopping and avoid distraction, men tend to prefer to minimize the shopping effort (Weijters et al., 2007). As stated by Venkatesh and Morris (2000), men tend to show a stronger attitudes toward instrumental IT applications than women. In this regard, Burke (2002) found that men were more interested to use in-store technologies which can increase their shopping efficiency in terms of time and effort required to shop. The general research on gender differences has also shown that men are more task-oriented and pragmatic than women (Minton and Schneider, 1985). On the other hand research on gender differences in the information technology indicates that the level of digital literacy differs between men and women in a way that women exhibit lower digital literacy than men (Lee and Huang, 2014) which adds to the perceived difficulty of using a new computer-based technology. Therefore it is expected that the performance related values of a technology will be more salient for men whereas effort related values will be more important for women (Venkatesh et al., 2003).

In addition, a solid stream of research on gender differences shows that women tend to value the social relations and others peoples' opinion to a higher degree than men (Becker, 1986; Miller, 1986). Evidence from technology acceptance research in different contexts leads to a similar conclusion; that is women attach more importance to others' opinions while deciding to use a novel information technology application (Guo, 2015; Venkatesh et al., 2012, 2003, 2000; Venkatesh and Morris, 2000; Zhang et al., 2014). On the contrary men tend to overlook the advices of others and make an independent decision (Becker, 1986; Miller, 1986); the tendency to make independent decisions rather based on the self-experience than others opinion leads to a presence of novelty seeking and openness trait regarding new technologies (Midgley and Dowling, 1978). Such novelty seeking in turn contributes to the hedonic motivation to use a novel technology (Holbrook and Hirschman, 1982). Therefore, female customers are more likely to be driven by social influence whereas male customers by hedonic motivation to use a new technology.

Consistent with UTAUT2 and based on the above-mentioned rationale as well as the evidence from the previous literature, it is expected that gender has a moderating effect on the relationships between behavior intention to use in-store ubiquitous computing-based information services and its antecedents. Thus, the hypotheses to be tested are:

H1.2: The influence of effort expectancy on behavior intention will be moderated by gender such that the effect will be stronger for women than for men

H2.2: The influence of performance expectancy on behavior intention will be moderated by gender such that the effect will be stronger for men than for women

H3.2: The influence of social influence on behavior intention will be moderated by gender such that the effect will be stronger for women than for men

H4.2: The influence of hedonic motivation on behavior intention will be moderated by gender such that the effect will be stronger for men than for women

4.4 Incorporating Contextual Factors – User Characteristics

As mentioned in section 4.1, after contextualizing the general theory (UTAUT2) based on the general service characteristics of in-store ubiquitous computing-based information services, the next step is the finer contextualizing of the general model regarding user, technology, and service characteristics.

User characteristics or individual factors account for the differences in certain characteristics of end users which might influence individuals' belief development process regarding a given technology. Emphasizing the importance of including the antecedent factors of the core beliefs in acceptance models, Yousafzai et al. (2007a) state that without a better understanding of the antecedents "*practitioners are unable to know which levers to pull in order to affect these beliefs and, through them, the use of technology*" (p. 268). Similarly Chin and Gopal (1995) advocate that "*greater understanding may be garnered in explicating the causal relationships between beliefs and their antecedent factors*" (p. 46).

Consistent with the practice in information system literature, this dissertation uses the definition of Agarwal and Prasad (1999) for individual differences: "*individual differences refer to user factors that include traits such as personality, demographic variables, as well as situational variables that account for differences attributable to circumstances such as experience*" (p. 362). As demographic variables of age and gender are already discussed in the previous sections. The focus of this section is only on individual differences originated in personality and situational variables, in the literature also referred to as non-demographic characteristics.

Incorporating user characteristics in technology acceptance studies is based on the rationale that supposing new technologies offer useful, easy, and fun to use services, the end users might perceive none of these advantages depending on what kind of users they are. The importance of the consideration of end user characteristics in the acceptance of new information technologies is repeatedly asserted in technology acceptance literature (e.g. Agarwal and Prasad, 1999, 1997; Benbasat and Zmud, 2003; Burton-Jones and Hubona, 2005; Y.-T. H. Chiu et al., 2010; Karahanna et al., 2002; Kwon et al., 2007). General technology acceptance models as well as their origins often focus on direct determinants of the behavior and don't comprehensively specify how technology related beliefs are formed. However, they introduced a place holder construct emphasizing the importance of tracing back the impact of factors which influence intentions and behavior indirectly through proximal beliefs, especially while developing a context-specific theory. For example in TRA and TPB a class of variables has been introduced, respectively called external variables and background factors (such as personality, broad life values, and exposure to media or other sources of information), influencing behavior indirectly by their effects on beliefs (Ajzen, 2011) (see Figure 6 and Figure 8). Similarly TAM introduces a general construct named as external variables determining the belief system (see Figure 9). Davis et al. (1989) even state that "*a key purpose of TAM (…) is to provide a basis for tracing back the impact of external factors on internal beliefs, attitudes and intentions*" (p. 985).

In the context of retailing, the consideration of user characteristics is especially important as retailers often serve several customer segments and it is crucial to discover whether the decision of acceptance or rejection of a new technology is affected by the type of the user (Kwon et al., 2007) and whether individual differences influence the formation of the beliefs. Therefore Y.-T. H. Chiu et al. (2010) urge retailers to take a segment-oriented approach while introducing novel retail technologies. For example, perceptions of a technology's ease of use might differ between innovative and non-innovative customers or a more assistant sensitive customer can find an in-store technology-based assistant service more useful. Examining which characteristics are useful for the market segmentation is crucial and hence should be considered in implementing in-store ubiquitous computing technologies. Incorporating user characteristics into the acceptance model as antecedents of beliefs has valuable managerial implications as mangers would be able to profile individuals and either target only individuals with positive beliefs and/or develop marketing measures to proactively intervene in belief development process by influencing such factors.

However from the 13 studies in the acceptance of in-store ubiquitous computing-based information services listed in Table 9, only three studies have included individual variables in their models. Adding three individual variables of self-efficacy, personal innovativeness, and perceived sensitivity as the antecedents of TAM constructs. Studying the acceptance of mobile shopping assistance systems in the point of sale, Kwon et al. (2007) concluded that personal innovativeness and self-efficacy has a positive significant effect on perceived ease of use of mobile shopping assistance. Rothensee (2010) included dominance and technical competence to his TAM-based model of ubiquitous computing acceptance (UbiTAM); the findings showed that however dominance played no role in acceptance of in-store ubiquitous computing technologies, technical competence had a significant influence on customers' perceived ease of use. In their infamous article introducing UTAUT2, Venkatesh et al. (2012) call for further research on extending UTAUT2 by incorporating user characteristics as exogenous predictors of the UTAUT2 core variables.

In their meta-analysis of TAM-based studies Yousafzai et al. (2007a) listed 24 user-specific variables used in the literature. From which personal innovativeness, self-efficacy and user experience are the most frequently adopted factors (Kwon et al., 2007, p. 483). Given a large number of potential individual factors, it is recommended in the literature to use the context-specific theory to guide the selection of important background factors in the behavioral domain of interest (Albarracin and Ajzen, 2007; W. Hong et al., 2013).

Based on the context being studied, two classes of individual characteristics have been identified as the most relevant for the purpose of this study that is the Internet dependency relations (action orientation, interaction orientation, social play, and solitary play), personal innovativeness, and involvement (relevance and importance). The remainder of this chapter is dedicated to the theoretical rationale for the relevance of these factors to the context and core constructs of the general model.

4.4.1 Incorporating Internet Dependency into UTAUT2

One of the objectives of this dissertation is to explore the potential influences of the expanding trend of the Internet use as the information medium on the user acceptance of in-store ubiquitous computing-based information services. The previous literature suggests that customers make their information channel choices based on their prior experience (Verhoef et al., 2009) and the experience of searching online has raised the expectation bar for services in offline retail so that today customers expect a more easy-to-access, easy-to-evaluate and transparent information (Burke, 2010). Thus it is logical to assume that based on the information service similarities between the Internet and the in-store ubiquitous computing-based information services, customers who use the Internet and have prior desirable experiences with it would evaluate the in-store ubiquitous computing information services more positively and consequently be more keen to use them.

To be able to theoretically integrate this assumption into the dissertation's base model, the mass media effects research has been explored in section 3.2 and the applicability of the individual media dependency theory on analyzing and measuring the effects of the Internet on individuals has been discussed (see section 3.2.3). It has been concluded that the individual media dependency theory offers a salient theoretical framework to identify the effects that the use of the Internet as an information medium can cause on individuals and understand why such effects differ between individuals.

As discussed in section 3.2.2.2, MSD theory perceives individuals as having three general types of goals, namely understanding, orientation, and play (Ball-Rokeach et al., 1984; Grant et al., 1991). Accordingly individual's motivations to use media information resources is in order to attain these goals (Ball-Rokeach, 1998; DeFleur and Ball-Rokeach, 1989). Therefore, the individual media dependency typology proposed by the theory consists of three dimensions, each of which in turn comprises of a personal and social dimension resulting in six different types of media dependency relations (see Table 10). Thus applying the MSD theory to the Internet as an information medium, in this dissertation a multidimensional approach has been taken to conceptualize the effects of the Internet information use on the individuals. However, based on the definition of the understanding dimension, which is the dependency relationship of audience members on the Internet information resources in order to establish knowledge and meaningful interpretations of themselves and their social environs, has been identified as irrelevant to the context of in-store ubiquitous computing-based information services.

As a result, four factors from orientation and play dimensions of the Internet dependency are identified which are expected to play a direct role in customers' belief formation regarding the in-store ubiquitous computing-based information services. These factors are listed in Table 13 along with their definitions.

Table 13: User characteristics – Internet media dependency relations

External Factors – User Characteristics	Definition
Action orientation	The degree to which an individual is dependent on the Internet information resources to take a purchasing decision
Interaction orientation	The degree to which an individual is dependent on the Internet information resources to communicate with others
Social play	The degree to which an individual is dependent on the Internet resources to satisfy her hedonic goals associated with interaction between individuals
Solitary play	The degree to which an individual is dependent on the Internet resources to satisfy her solely individual hedonic goals

Figure 21 shows the process of incorporating these factors into the base model. In the following sections, the theoretical rationale to incorporate the orientation and play dimensions of the Internet dependency relations into the base model of this dissertation would be thoroughly discussed followed by the formulation of each theoretical relationship as a research hypothesis.

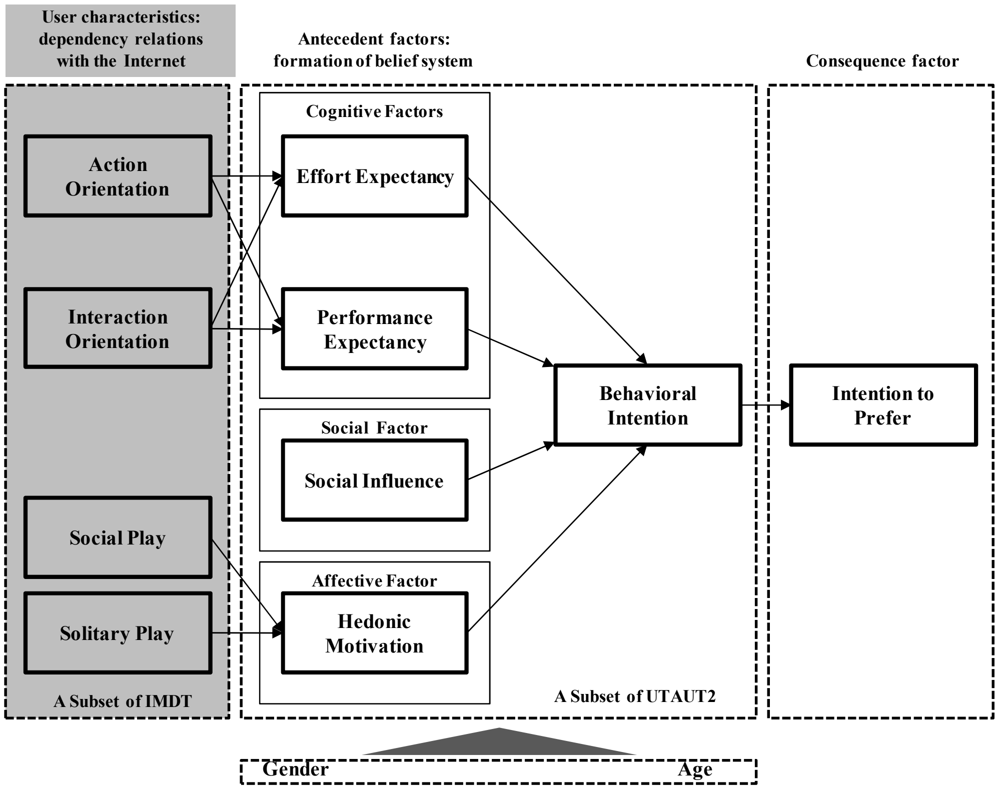


Figure 21: Incorporating the Internet media dependency relations into the base model

4.4.1.1 Internet Dependency to Fulfill Orientation goals

While introducing their theory of reasoned action (see section 3.1.1.1), Fishbein and Ajzen (1975) noted that "*belief formation should follow the laws of learning*" (p. 29). The law of proactive inhibition (McGeoch and Irion, 1952) from human associative view of learning postulates that individuals' prior experiences (positively or negatively) intervene in their capability to learn to exhibit novel behaviors. The magnitude and direction of intervention is dependent on the similarity relationship between the structure of the existing and novel behavior (Gick and Holyoak, 1987). That is the extent of similarity (dissimilarity) of individuals' prior experiences with the behavior under learning positively (negatively) influences the extent of their learning (Gick and Holyoak, 1987). Synthesizing the literature in both social psychology and learning theories, Agarwal and Prasad (1999) concluded that "*factors that might influence the formation of beliefs are posited to be the same as those that influence learning processes*" (p. 366). Thus similar prior experiences which leads to enhanced learning may result in more positive beliefs regarding the new behavior (Agarwal and Prasad, 1999).

In technology acceptance literature, the role of prior experience in formation of the individual's technology related belief system has long been recognized. Consistent with the learning theories, it is believed that previous experiences with similar technologies result in formation of more positive beliefs and consequently more favorable attitudes toward using a new technology (Agarwal and Prasad, 1999; Lu et al., 2003). Yet the majority of studies which included prior experience in their models refer to it as a repetition of the exact same behavior that is based on the absolute similarity of the existing and novel task (Chau, 1996; Hernández et al., 2010; Igbaria et al., 1995; June Lu et al., 2003; Taylor and Todd, 1995a).

However there are also few studies which have used the prior experience in terms of relative similarity of the technologies; developing a TAM based model, Agarwal and Prasad (1999) hypothesized that the extent of prior experience with similar technologies is positively associated with ease of use and usefulness beliefs about an information technology innovation. They have conducted an empirical study in organizational settings to test their hypotheses; the stimulus in the study was a newly introduced operating system with graphical user interface environment. To assess the prior familiarity with similar technologies, the study used three stimuli because of their similarity and relevance to the technology being examined, namely level of familiarity with personal computers, prior usage of graphical user interfaces, and prior usage of input devices as computer mouse. Based on the empirical results, individuals who hold greater experiences with similar technologies found the new technology easier to use. However, the study could not support the direct relationship between the prior experience and usefulness.

Developing an acceptance model for in-store technology-based self-service options Dabholkar (1996) postulated that the attitude toward using technological products in general has a positive effect on service quality evaluation of technology-based self-service options and in turn the expected service quality positively influences the intention to use. He used the notion of prior similar experience to theoretically justify the relationship between attitude and expected service quality noting that when individuals encounter a new technology with which they don't have a personal experience, they tend to evaluate and make decisions drawing on the compatible prior experiences. Thus individuals who have used technology products and have formed a favorable attitude towards them will evaluate new, but similar, technologies more positively. To test the hypotheses, a scenario based empirical study was conducted. The stimulus was a computerized, touch screen to order a meal in a fast food restaurant. For prior experience with similar technologies and resulting attitude, participants were asked about their experience concerning the computers in general and ATMs in particular. The hypothesized relationships could be supported by empirical data.

Based on the studies reported above, it can be assumed that it is not prior experience in terms of frequency and extent of usage but the resulted attitude which builds a salient foundation for the evaluation of the similar new technologies. For example Agarwal and Prasad (1999) only used level of usage and familiarity with technologies to measure the similar prior experience; apparently the level of similar technology usage influenced individual's technology perception concerning the ease of use but had no direct effect on their perception of its utilitarian benefits. However, Dabholkar (1996) added the notion of attitude toward using similar technology products to the concept of prior experience. They could empirically show that individuals' experience based favorable attitude towards a technology positively influences their utilitarian and affective beliefs regarding new, but similar, technologies.

In-store ubiquitous computing technologies are not yet widely spread thus many customers do not have a direct experience with them; based on the above-mentioned arguments, it is expected that in the absence of a direct system experience consumers past experiences with similar technologies will serve as the basis for their perceptions about how easy, how useful or how enjoyable the new technologies are. As discussed in section 2.2, in-store ubiquitous computing based services are similar to the Internet based information services. Individuals who have used the Internet as an information medium have formed an attitude toward it ranging from very favorable to very unfavorable. Therefore, it can be postulated that the favorable attitude toward using internet information services will have a positive effect on the cognitive and affective beliefs concerning the in-store ubiquitous computing-based information services.

In the previous literature, the conceptualization of the prior experience and the resulting attitude often is missing the theoretical underpinning and thus lacking a theory-driven approach for its measurement (Varma, 2010).

No specific definition of experience has been provided to date. Considering the key role of experience in understanding the belief–intention–acceptance relationship, researchers might use *more finely grained of detail in its conceptualization of experience. Domain specific conceptualization of experience should be addressed. (Sun and Zhang, 2006, p. 69)*

Therefore, in this research individual media dependency theory has been chosen for conceptualization of the prior Internet experience and resulting favorable attitude.

It can be argued that, in the context of this study, individual media dependency theory offers the best proxy for conceptualization of the prior Internet experience and resulting favorable attitude. First of all, it postulates that when it comes to information media, prior experience in terms of extent and frequency of use alone cannot define the sustainable consequences of media use on individual's attitude toward the media. Second, individual media dependency theory offers a salient theoretical framework to identify the effects that the usage of the Internet as an information medium can cause on individuals and understand why such effects differ between individuals. Third, it manifests a dimensional relationship between the person and medium allowing a more comprehensive evaluation of media use effects.

Therefore, building on the above mentioned discussions, it can be postulated that the intensity of the general Internet dependency relations would significantly influence individuals' cognitive and affective perceptions of the in-store ubiquitous computing-based information services.

Two orientation dimensions of media dependency, namely action and interaction orientation are likely to positively influence the performance and effort expectancy beliefs. Orientation media dependency dimension stems from the individual motivation to obtain the necessary decision-making guidance from the information resources of a given media in order to behave correctly, whether on the personal level or with others. Based on MSD theory, IMD relations are function of goals and perceived utility value of media's information resources (Ball-Rokeach, 1985; Ball-Rokeach and Jung, 2009; Grant et al., 1991). That is an individual who is dependent on Internet information resources to fulfill her orientation goals has already experienced the advantages of the Internet information resources to attain her orientation goals and holds positive beliefs about its instrumental value. Based on the notion of prior experience, when individuals encounter a new technology, past favorable experiences with similar technologies will serve as the basis for their perceptions. In addition in media research, considerable evidence amassed which show that users perceive new similar communication technologies just as extensions of the existing ones and evaluate them on the bases of their experience with the existing technologies (Williams et al., 1985).

From the utilitarian perspective, Riffe et al (2008, p. 4) refer to four characteristics of the Internet which are responsible for its spread and micro-level dependency of individuals:

- *The Internet features almost instantaneous delivery of information, which makes it faster than traditional media.*
- *The Internet is interactive, which allows more immediate feedback than any other medium.*
- *The Internet allows for the distribution of multimedia content which many media do not.*
- *The Internet allows for the distribution of large amounts of low-cost, in-depth information.*

Although in a different scale, the information related advantages of the Internet can be also listed for in-store ubiquitous computing based information services (see section 2.2). Therefore, it is expected that individuals who are dependent on the Internet to fulfill their orientation goals would extend the instrumental value of the Internet to the in-store ubiquitous computing information services. Performance expectancy stands for the perceived instrumental value obtained from the use of technology. Thus it is expected that the level of action orientation dependency of customers resulting from usage experiences of the Internet information sources will be positively associated with the customers' beliefs concerning the performance expectancy of in-store ubiquitous computing information services. Furthermore, formation of the dependency relations is contingent upon the development of the required skills to use the media. Thus, individuals who are dependent on internet to fulfill their orientation goals perceive no cognitive burden caused by the Internet itself. Again referring to the concept of prior experience with similar technologies, it is expected that the level of action orientation dependency of customers resulting from usage experiences of the Internet information sources will be positively associated with the customers' beliefs concerning the effort expectancy of in-store ubiquitous computing information services. Based on the above-mentioned rationale and considering two, action and interaction, dimensions of the orientation the hypotheses to be tested are:

H6: Action orientation dependency of customers on the Internet has a significant positive effect on effort expectancy of in-store ubiquitous computing-based information services.

H7: Action orientation dependency of customers on the Internet has a significant positive effect on performance expectancy of in-store ubiquitous computing based information services.

H8: Interaction orientation dependency of consumers on the Internet has a significant positive effect on effort expectancy of in-store ubiquitous computing based information services.

H9: Interaction orientation dependency of consumers on the Internet has a significant positive effect on performance expectancy of in-store ubiquitous computing based information services.

4.4.1.2 Internet Dependency to Fulfill Play goals

Based on the classic theory of schema-triggered affect (Fiske, 1982), if individuals identify a new object as an instance of, a prior experience-based, affectively weighted category, they will automatically evaluate the instance on the bases of the associated affect with the category and apply it to the newly encountered object (Fiske and Pavelchak, 1986; Fiske and Taylor, 2013). Building on this theory, to evaluate the in-store ubiquitous computing-based information services, customers will try to fit these technologies in their previously defined categories. Based on the similarity of the services, the Internet as an information medium can be defined as the reference category for information search and evaluation support services. Therefore, a customer who has affective dependency relationships with the Internet will also apply it to in-store ubiquitous computing information services. In other words, positive emotions concerning the Internet would lead to positive emotions concerning the in-store ubiquitous computing information services. Thus it is expected that users who are dependent on the Internet for performing their play related actions would have a higher perceived hedonic value of in-store ubiquitous computing based information services. Considering two, social and solitary, dimensions of the play the hypotheses to be tested are:

H10: Social play dependency of customers on the Internet has a significant positive effect on hedonic motivation of in-store ubiquitous computing-based information services

H11: Solitary play dependency of customers on the Internet has a significant positive effect on hedonic motivation of in-store ubiquitous computing-based information services

4.4.2 Incorporating Personal Innovativeness and Involvement into UTAUT2

In addition to the IMDT relations, reviewing the relevant user characteristics in the consumer context, two additional user characteristics namely personal innovativeness and involvement (relevance and importance) are identified as relevant for the context of this dissertation. These factors are listed in Table 14 along with their definitions.

Table 14: User characteristics – personality traits

External Factors – User Characteristics	Definition
Personal innovativeness in IT	The degree to which an individual is willing to try out any new information technology
Relevance	The degree of an individual's general dedication and interest in making informed purchasing decisions
Importance	The degree of intrinsic desire or personal need for information support while purchasing a product

Figure 22 shows the process of incorporating these factors into the base model. In the following sections, the theoretical rationale to incorporate these factors into the base model of this dissertation would be thoroughly discussed followed by the formulation of each theoretical relationship as a research hypothesis.

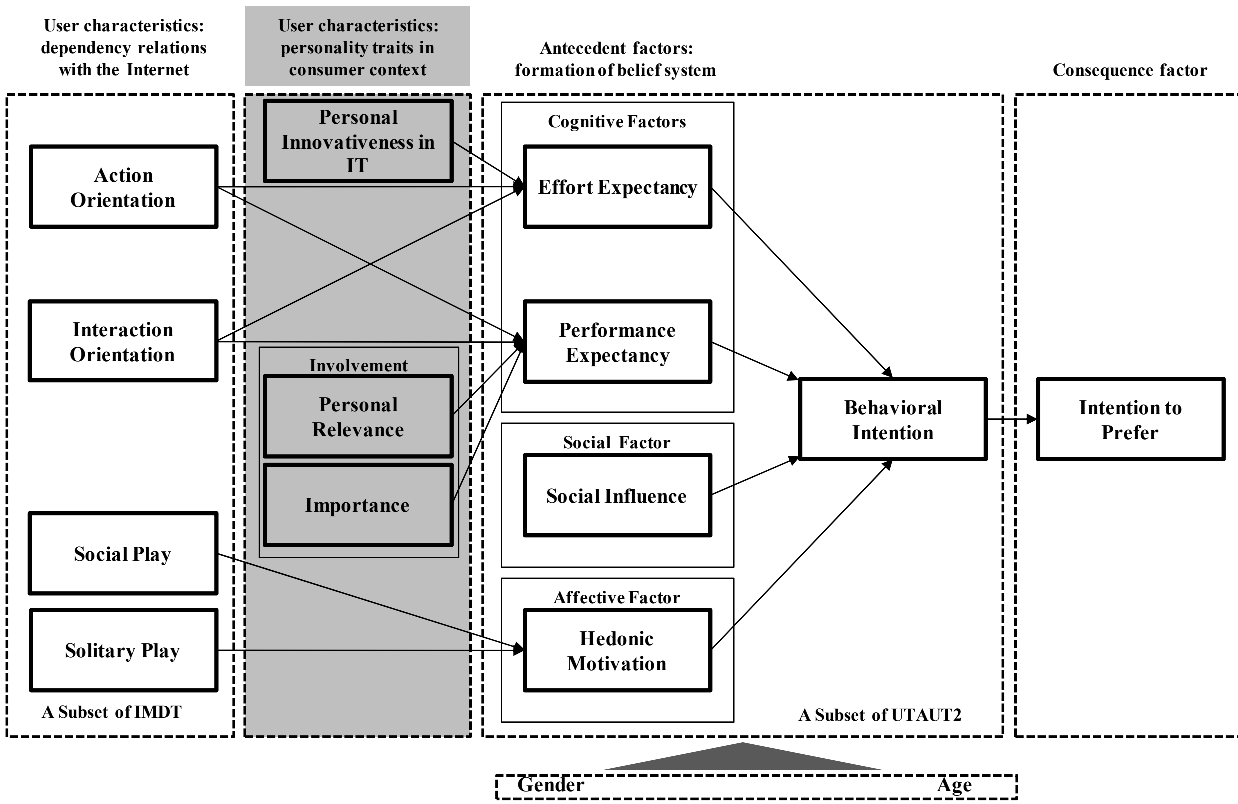


Figure 22: Incorporating the personal innovativeness and involvement into the base model

4.4.2.1 Personal Innovativeness in Information Technology

Innovativeness has long been considered in marketing and consumer behavior research (Hirschman, 1980; Midgley and Dowling, 1978; Rogers, 1983) as a personality trait which to a greater or lesser degree is existent in every individual (Midgley and Dowling, 1978). Hirschman (1980) justifies the existence of innovativeness trait by emphasizing that "*if there were no such characteristic as innovativeness, consumer behavior would consist of a series of routinized buying responses to a static set of products*" (p. 283). Midgley and Dowling (1978) define the concept of innovativeness as "*the degree to which an individual is receptive to new ideas and makes innovation decisions independently of the communicated experience of others*" (P. 236). Innovation itself is defined as "*an idea, practice, or object perceived as new by the individual*" (Rogers and Shoemaker, 1971, p. 19).

In general acceptance research, the propensities of individuals to adopt novel goods and services has as well an important meaning. In innovation diffusion research (see section 3.1), it has been acknowledged that individuals with higher degree of innovativeness are active information seekers of novel ideas and possess higher risk-taking propensity; therefore they can cope with high levels of uncertainty associated with new ideas and develop more positive attitude toward their acceptance and use (Rogers, 2010, 1983).

In empirical research, two different conceptualization approaches have been evolved around the notion of personal innovativeness namely global and domain specific. The global approach focuses merely on individuals' cognitive style postulating that an individual who scores high on innovative cognitive style will be more likely to accept any novel product independent from the domain and product category. However, in empirical studies on specific adoption decisions, the global view of innovativeness revealed low predictive power (Gatignon and Robertson, 1985; Goldsmith and Hofacker, 1991; Leonard-Barton and Deschamps, 1988). As a result, researchers have developed a domain specific approach in which the personal innovativeness concept was tailored to a specific domain of interest; despite the global innovativeness, domain specific innovativeness could exhibit better predictions of adoption of innovations by consumers when applied in a specific domain of innovation (Agarwal and Prasad, 1998; Goldsmith and Hofacker, 1991; Yi et al., 2006).

Consistent with the marketing and general innovation adoption literature, the notion of innovativeness has received a notable attention in technology acceptance studies as one of the key individual differences influencing the decision of acceptance and use of an innovative technology. Agarwal and Prasad (1998) developed a domain specific conceptualization of personal innovativeness for predicting information technology acceptance. Based on the definition of Midgley and Dowling (1978), they defined the personal innovativeness in the domain of information technology as "*the willingness of individual to try out any new information technology*" (p. 206).

Agarwal and Prasad (1998) postulated that individuals with higher degree of innovativeness in regard to information technology will develop more positive cognitive beliefs (ease of use and usefulness) about the technology innovation and consequently will have higher intention to accept the new technology under question. Using TAM as their base model, they have incorporated the notion of innovativeness as a moderator of TAM's main relationships; empirical results could support the hypothesized relationships. Yi et al. (2006) examined two alternatives TAM-based models, one with the innovativeness in the role of moderator of belief-intention relationships and the other with the innovativeness as direct determinant of cognitive beliefs (usefulness and ease of use). Empirical comparison of the models showed that personal innovativeness was a direct determinant of beliefs; however, it had a very small and nonsignificant effect as a moderator. The direct positive impact of personal innovativeness in IT on cognitive beliefs of ease of use and usefulness has been empirically tested by various studies in different technology contexts (Kuo and Yen, 2009; Lu, 2014; Lu et al., 2005, 2003; Rai et al., 2013; Van Raaij and Schepers, 2008). However the direct and positive impact of innovativeness on ease of use has been supported, the hypothesized relationship between innovativeness and usefulness were often empirically rejected (Kuo and Yen, 2009; Van Raaij and Schepers, 2008). More notably, in the context of in-store ubiquitous computing technologies, Kwon et al. (2007) postulated direct positive impacts of personal innovativeness on both ease of use and usefulness while developing a model for user acceptance of mobile shopping assistance. Based on the empirical results, they could only find a significant effect of innovativeness on ease of use. Building on the previous empirical results, in this study only the impact of innovativeness on ease of use is hypothesized.

Innovative people are more likely to try an innovation in early stages of its introduction (Agarwal and Prasad, 1998; Lu et al., 2003; Rogers, 2010). As in-store ubiquitous computing information technologies are currently at very early stages of diffusion, it is expected that most individuals do not have any or much knowledge and experience for formation of their beliefs. Therefore, the risk taking and curious personalities in the domain of information technology who have more self-confidence to handle the new information technology may perceive the technology easier to use.

Given the strong theoretical basis and the evidence from the previous literature, it is expected that the personal innovativeness in information technology will be positively associated with the customers' beliefs concerning the ease of use of the in-store ubiquitous computing information services. Thus, the hypothesis to be tested is:

H12: Personal innovativeness in information technology has a significant positive effect on effort expectancy of in-store ubiquitous computing-based information services

4.4.2.2 Personal Involvement – Personal Relevance and Importance

In marketing and consumer research, involvement has been long recognized as an individual difference variable which influences the consumer purchase and communication behavior (Barki and Hartwick, 1994; Laurent and Kapferer, 1985; Zaichkowsky, 1985). The traditional consumer behavior theories were built based on the rational man assumption; which proposes that a consumer vigorously search for and comprehensively evaluate information to make an informed decision. However, in reality, different consumers search in different levels based on the subjective relevance and importance of the purchase decisions. As a result the notion of involvement has been introduced into the consumer behavior theories (Zaichkowsky, 1985). Contingent on the degree of consumers' involvement, consumers may differ greatly in the extent of their purchase decision process and information search. That is consumers' with higher involvement level regarding the purchase decisions search for more information and spend more time and effort for searching for the right selection (Zaichkowsky, 1985).

Barki and Hartwick (1994) define user involvement as "*a subjective psychological state, reflecting the importance and personal relevance of an object or event*" (p. 62). The object of involvement in this dissertation is the purchase decision; which reflects how interested consumers are about purchase decisions and how important it is for them to make the best decision.

Based on the definition of Barki and Hartwick (1994), involvement has two different facets, namely relevance and importance. Mayer (2012) argued that however relevance and importance are related concepts, depending on the context, their extent could differ for an individual. In his doctoral dissertation analyzing the acceptance of persuasive kitchen environments, he decomposed the involvement factor into two distinct factors of relevance and importance. These two factors were then incorporated as moderators in his model theorizing a positive moderating effect on the relationship between performance expectancy and behavioral intention. The moderating effect of importance could be supported by empirical results; however personal relevance had no significant moderating effect in this study.

In the context of this dissertation, importance is defined as the "the extent of intrinsic desire or personal need for information support while purchasing a product". Whereas relevance is defined as "the extent of an individual's general dedication and interest in making informed purchasing decisions", that is to which extent informed shopping in general is relevant to an individual. For example, making an informed purchase decision can be very relevant for a person, however getting help while shopping is not necessarily important for the same person due to her self-confidence on finding the right information on her own. Thus to specify more fully the nature of the relationship between the consumer and their purchase decision, in this dissertation the same approach as Mayer's has been taken. That is decomposing the involvement factor into relevance and importance dimensions.

One of the main objectives of the in-store ubiquitous computing information services is to assist consumers by searching for and evaluating the required information for their purchasing decision. In cognitive theories, it is argued that a system can be only considered as useful if a relationship between the use and its consequence is readily apparent (Venkatesh and Davis, 2000). Considering the personal relevance, it is expected that the consumers who are highly dedicated to make informed purchase decisions and thus are more willing to search and evaluate various product information find the systems more matching to their needs and therefore more useful. In regard to importance, it is expected that the consumers who need help and to whom it is important to get support while shopping will perceive the in-store ubiquitous computing information services more useful. Thus, the hypotheses to be tested are:

H13: Personal relevance of making an informed decision has a significant positive effect on performance expectancy of in-store ubiquitous computing-based information services.

H14: Importance of having shopping assistance has a significant positive effect on performance expectancy of in-store ubiquitous computing-based information services.

4.5 Incorporating Contextual Factors

Apart from individual characteristics, based on the diversity of in-store ubiquitous computing-based information services and technologies two additional contextual factors namely service type and technology type are added to the base model. Service type and technology type account for characteristics of tasks and technologies which might influence individuals' beliefs regarding a given service and technology. Figure 23 shows the process of incorporating these factors into the base model. In the following sections, the theoretical rationale to incorporate the system type and technology type as moderators into the base model of this dissertation will be thoroughly discussed followed by the formulation of each theoretical relationship as a research hypothesis.

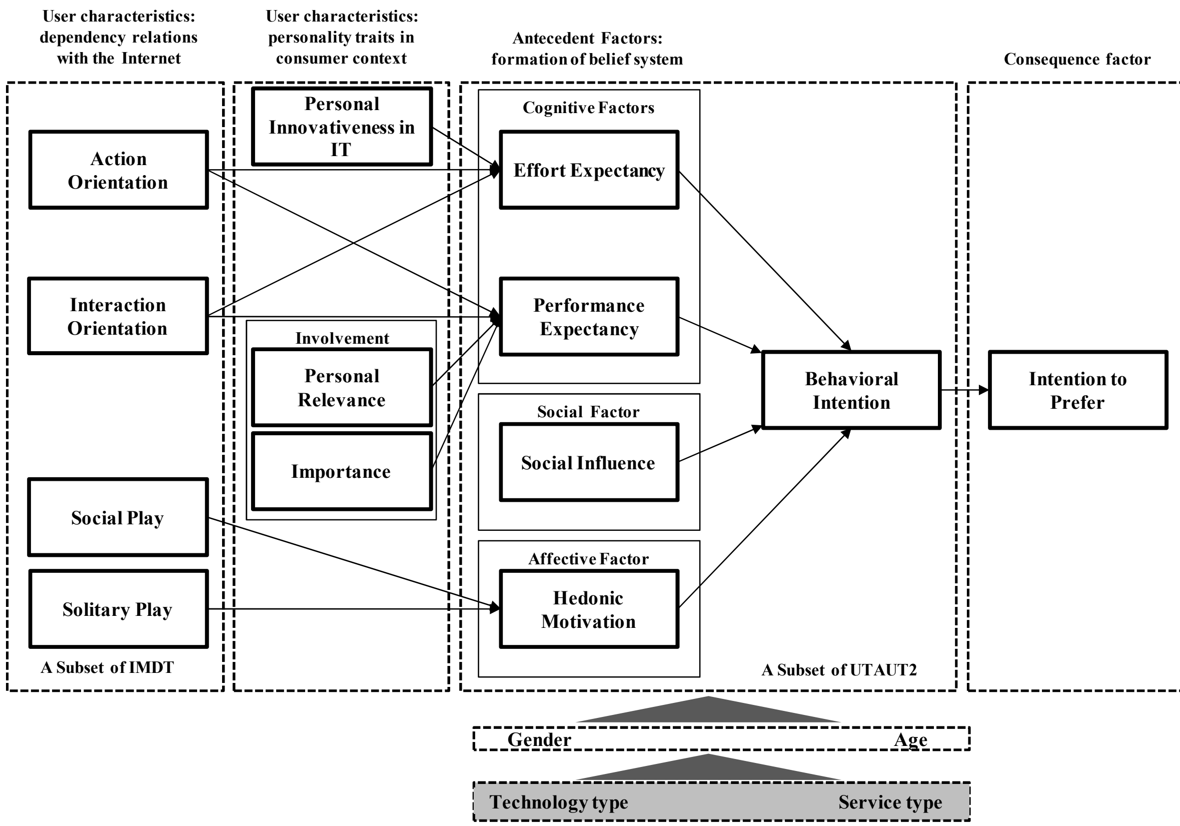


Figure 23: Incorporating service type and technology type into the base model

4.5.1 Service Type

In-store ubiquitous computing-based information services can be divided into two categories: assisting the information search and screening tasks and assisting the alternative evaluation tasks. Service type in this dissertation thus refers to these two service categories. Therefore, from the user's perspective, it represents the type of the task which is performed using the system, being it searching for product information or evaluation of the alternatives.

In behavioral theories task type has been identified as one of the important influencing factors on behavior as individuals' decision to perform a certain behavior may vary contingent on characteristics of the task (Hackman, 1969). Thus, in information system research, TAM-based models are criticized for overlooking the potential effects of task type on behavioral intention and use of new technologies (Gefen and Straub, 2000; Goodhue and Thompson, 1995). As a response, various studies have integrated the characteristics of task in their acceptance models, often as moderators of models' core constructs (D'Ambra and Wilson, 2004; Fang et al., 2005; Gefen and Straub, 2000; Sun and Zhang, 2006; Yen et al., 2010). The rationale for incorporating the task type in the acceptance models is derived from the task-technology fit model (Goodhue and Thompson, 1995); it postulates that individuals' needs are functions of task characteristics, therefore the fit between task requirements and service characteristics offered by a technology influences the users' system evaluation. The authors argued that as individuals have limited cognitive capacity, the more multifaceted and difficult a task, the less capacity would be left to deal with a system which then influences their evaluation of technology attributes (Goodhue and Thompson, 1995; Sun and Zhang, 2006).

Although interrelated, the information search and alternative evaluation stages are distinct in terms of needs. Whereas in the information search stage, customers conduct a more attribute-based search, in the alternative evaluation stage the focus is more in alternative-based search (Payne et al., 1993). As customers proceed in their decision making process, they stop to gather information about certain attributes and start to build a set of the most promising alternatives which then would be compared in more depth by processing bundles of product attributes and customer benefits (Payne et al., 1993, 1988). In addition, while becoming closer to the purchase decision, in alternative evaluation stage the effect of possible undesirable consequences of a faulty choice is most comprehended by customers (Tversky and Kahneman, 1981). Therefore, in general the alternative evaluation is perceived as a more complex task than information search (Payne et al., 1993, 1988).

According to task-technology fit model, task complexity negatively influences the users' perception regarding the match between the technology capabilities and task demands (Dishaw and Strong, 1999; Frambach et al., 2007). Therefore, it can be assumed that because of the relative complexity of alternative evaluation, users will perceive assisting technologies more compatible with searching and screening the product information than evaluating the alternatives. Current empirical research can support this assumption; regarding the online technology, research shows that online channel is more compatible with customers' needs in information search than alternative evaluation stage; as by increasing complexity customers tend to seek expert help in offline stores (Frambach et al., 2007). In addition, Karaatli et al. (2010) investigated the user perception of mobile based shopping assistance services at different stages of the consumer decision making. Based on their findings, more customers believed that mobile services can improve their shopping experience in information search stage than alternative evaluation stage. However, they haven't addressed the potential effect of this perception on customers' technology evaluation and use.

Building on the task-technology fit model and assuming a better fit between the assisting technologies and information search tasks than alternative evaluation tasks, it is expected that customers evaluate in-store ubiquitous computing-based services differently. Based on task-technology fit model, the more complex the task, the less cognitive capacity a user can allocate for operating the technology (Goodhue and Thompson, 1995; Sun and Zhang, 2006). Therefore, it is expected that effort expectancy would be more important for the acceptance of the alternative evaluation services than information search services. In contrast, empirical results show that the higher fit between the task and technology leads to a more positive beliefs concerning the relative advantage of the system (Fang et al., 2005; Goodhue and Thompson, 1995; Klopping and McKinney, 2004; Yen et al., 2010; Zhou et al., 2010). Considering the two cognitive and hedonic dimensions of the relative advantage, it is expected that customers would perceive the information search services more useful and fun than alternative evaluation stages. As said, while becoming closer to the purchase decision, in alternative evaluation stage the effect of possible undesirable consequences of a faulty choice is most comprehended by customers (Tversky and Kahneman, 1981). Therefore, it is expected that customers place relatively less weight on the opinions of important others while making the decision to use the alternative evaluation services.

Based on above mentioned arguments, it is expected that service type has a moderating effect on the relationships between behavior intention to use in-store ubiquitous computing based information services and its antecedents. Thus, the hypotheses to be tested are:

H1.3: The influence of effort expectancy on behavior intention will be moderated by service type such that the effect will be stronger for services assisting alternative evaluation stage

H2.3: The influence of performance expectancy on behavior intention will be moderated by service type such that the effect will be stronger for services assisting information search stage

H3.3: The influence of social influence on behavior intention will be moderated by service type such that the effect will be stronger for services assisting information search stage

H4.3: The influence of hedonic motivation on behavior intention will be moderated by service type such that the effect will be stronger for services assisting information search stage

4.5.2 Technology Type

As discussed in section 2.2, different technologies have been developed to assist customers through information search and alternative evaluation process in brick and mortar retail. Based on the technology device ownership, these technologies can be divided in two main categories namely store-based systems (Melià-Seguí et al., 2013; Pantano, 2010b; Pantano and Naccarato, 2010) and applications based on customers own smart mobile devices (Gao et al., 2010; Kowatsch et al., 2011; Kowatsch and Maass, 2010). The types of services provided by store-based systems are replicable on customers own mobile devices. As the level of investment on store-based systems is significantly higher than mobile applications, it is important for retailers to know if customers perceive and evaluate these technologies differently. In this regard, Pantano (2014b) argues that, as current models fail to investigate the potential effect of technology type on customers' usage decisions, they are unable to provide retailers with a guideline on which is the best technology to invest in and calls for further research on this topic. Therefore, as the last factor, technology type is incorporated in the conceptual model as a moderator of the relationships between the behavioral intention and its direct antecedents. The rationale for this integration is elaborated below.

Technology device ownership is believed to increase the acceptance likelihood of new applications based on the already owned device (Niehaves et al., 2012; Tretiakov and Kinshuk, 2005). Several studies assume that the acceptance of advanced mobile services such as mobile commerce, mobile learning, and mobile internet is positively influenced by the customers prior mobile device use (Lu et al., 2003; Wang et al., 2009; Wu and Wang, 2005).

In general, users feel more confident using their own devices while being engaged in a new context as obtained experience and skills from the previous usage can be easily utilized in the new context (Prete et al., 2011). Empirical research shows that with increasing experience and skill, the importance of the ease of using a system as well as hedonic and social motivations for its use fades (Venkatesh et al., 2012, 2003). Therefore, it is expected that customers place less weight on the effort expectancy, hedonic motivation, and social influence while evaluating in-store information services provided on their own mobile devices. In contrast, individuals appear to place a greater utilitarian value on technologies they have chosen to own (Conole, 2008; Jeffery, 2013; Yen et al., 2010). Therefore, they might associate more utilitarian value with in-store information services provided on their own mobile devices than the ones installed in the store.

Based on the above mentioned arguments, it is expected that technology type has a moderating effect on the relationships between behavior intention to use in-store ubiquitous computing-based information services and its antecedents. Thus, the hypotheses to be tested are:

H1.4: The influence of effort expectancy on behavior intention will be moderated by technology type such that the effect will be stronger for store-owned devices.

H2.4: The influence of performance expectancy on behavior intention will be moderated by technology type such that the effect will be stronger for user-owned mobile devices.

H3.4: The influence of social influence on behavior intention will be moderated by technology type such that the effect will be stronger for store-owned devices.

H4.4: The influence of hedonic motivation on behavior intention will be moderated by technology type such that the effect will be stronger for store-owned devices.

4.6 Summary of Hypotheses

To develop a contextual acceptance model for in-store ubiquitous computing based information services, UTAUT2 has been chosen as the base model. After refining the UTAUT2 based on the context requirements, four factors are defined as the most important direct determinants of behavioral intention. The base model was then extended step by step by integrating various aspects of the context. 10 variables have been added to the base model (Table 15 offers a summary of these factors including the factors from the base mode) resulting in formulation of 30 hypotheses (Table 16 offers a summary of all developed hypotheses). Figure 24 shows the final conceptual model of this dissertation

Table 15: Summery of the factors used in the conceptual model of this dissertation

Factors	Definition
Behavioral intention	The degree to which a customer would use in-store ubiquitous computing-based services if available
Performance expectancy	The degree to which using in-store ubiquitous computing-based information services will provide benefits to customers in performing certain activities
Effort expectancy	The degree of ease associated with customers' use of in-store ubiquitous computing-based information systems
Social influence	The degree to which a consumer perceives that important others believe he or she should use the new system.
Hedonic motivation	Fun or pleasure derived from using the in-store ubiquitous computing-based information systems
Intention to prefer	The degree to which users will prefer a retail store which offers in-store ubiquitous computing-based information services
Action orientation	The degree to which an individual is dependent on the Internet information resources to take a purchasing decision
Interaction orientation	The degree to which an individual is dependent on the Internet information resources to communicate with others
Social play	The degree to which an individual is dependent on the Internet resources to satisfy her hedonic goals associated with interaction between individuals
Solitary play	The degree to which an individual is dependent on the Internet resources to satisfy her solely individual hedonic goals
Personal innovativeness in IT	The degree to which an individual is willing to try out any new information technology
Relevance	The degree of an individual's general dedication and interest in making informed purchasing decisions
Importance	The degree of intrinsic desire or personal need for information support while purchasing a product
System type	The type of the task which is performed using the system (information search vs. alternative evaluation)
Technology type	The type of the technology through which in-store information services are offered (user owned mobile device vs. store-owned devices)

Table 16: Summery of hypotheses on the acceptance determinants of in-store ubiquitous computing-based information services

Hypothesis	Relationship
H1	Effort expectancy has a significant positive effect on behavior intention to use in-store ubiquitous computing-based information services
H1.1	The influence of effort expectancy on behavior intention will be moderated by age such that the effect will be stronger for older people than younger people
H1.2	The influence of effort expectancy on behavior intention will be moderated by gender such that the effect will be stronger for women than for men
H1.3	The influence of effort expectancy on behavior intention will be moderated by service type such that the effect will be stronger for services assisting alternative evaluation stage
H1.4	The influence of effort expectancy on behavior intention will be moderated by technology type such that the effect will be stronger for store-owned devices.
H2	Performance expectancy has a significant positive effect on behavior intention to use in-store ubiquitous computing-based information services.
H2.1	The influence of performance expectancy on behavior intention will be moderated by age such that the effect will be stronger for younger people than older people
H2.2	The influence of performance expectancy on behavior intention will be moderated by gender such that the effect will be stronger for men than for women
H2.3	The influence of performance expectancy on behavior intention will be moderated by service type such that the effect will be stronger for services assisting information search stage
H2.4	H2.4: The influence of performance expectancy on behavior intention will be moderated by technology type such that the effect will be stronger for user-owned mobile devices.
H3	Social influence has a significant positive effect on behavior intention to use in-store ubiquitous computing-based information services.
H3.1	The influence of social influence on behavior intention will be moderated by age such that the effect will be stronger for older people than younger people
H3.2	The influence of social influence on behavior intention will be moderated by gender such that the effect will be stronger for women than for men
H3.3	The influence of social influence on behavior intention will be moderated by service type such that the effect will be stronger for services assisting information search stage
H3.4	The influence of social influence on behavior intention will be moderated by technology type such that the effect will be stronger for store-owned devices.
H4	Hedonic motivation has a significant positive effect on behavior intention to use in-store ubiquitous computing-based information services.
H4.1	The influence of hedonic motivation on behavior intention will be moderated by age such that the effect will be stronger for younger people than older people
H4.2	The influence of hedonic motivation on behavior intention will be moderated by gender such that the effect will be stronger for men than for women
H4.3	The influence of hedonic motivation on behavior intention will be moderated by service type such

Hypothesis	Relationship
	that the effect will be stronger for services assisting information search stage
H4.4	The influence of hedonic motivation on behavior intention will be moderated by technology type such that the effect will be stronger for store-owned devices.
H5	Behavior intention to use in-store ubiquitous computing based information services has a significant positive effect on customers' preference of stores offering such services.
H6	Action orientation dependency of customers on the Internet has a significant positive effect on effort expectancy of in-store ubiquitous computing-based information services.
H7	Action orientation dependency of customers on the Internet has a significant positive effect on performance expectancy of in-store ubiquitous computing-based information services.
H8	Interaction orientation dependency of consumers on the Internet has a significant positive effect on effort expectancy of in-store ubiquitous computing-based information services.
H9	Interaction orientation dependency of consumers on the Internet has a significant positive effect on performance expectancy of in-store ubiquitous computing-based information services.
H10	Social play dependency of customers on the Internet has a significant positive effect on hedonic motivation of in-store ubiquitous computing-based information services
H11	Solitary play dependency of customers on the Internet has a significant positive effect on hedonic motivation of in-store ubiquitous computing-based information services
H12	Personal innovativeness in IT has a significant positive effect on effort expectancy of in-store ubiquitous computing-based information services.
H13	Personal relevance of making an informed decision has a significant positive effect on performance expectancy of in-store ubiquitous computing-based information services.
H14	Importance of having shopping assistance has a significant positive effect on performance expectancy of in-store ubiquitous computing-based information services.

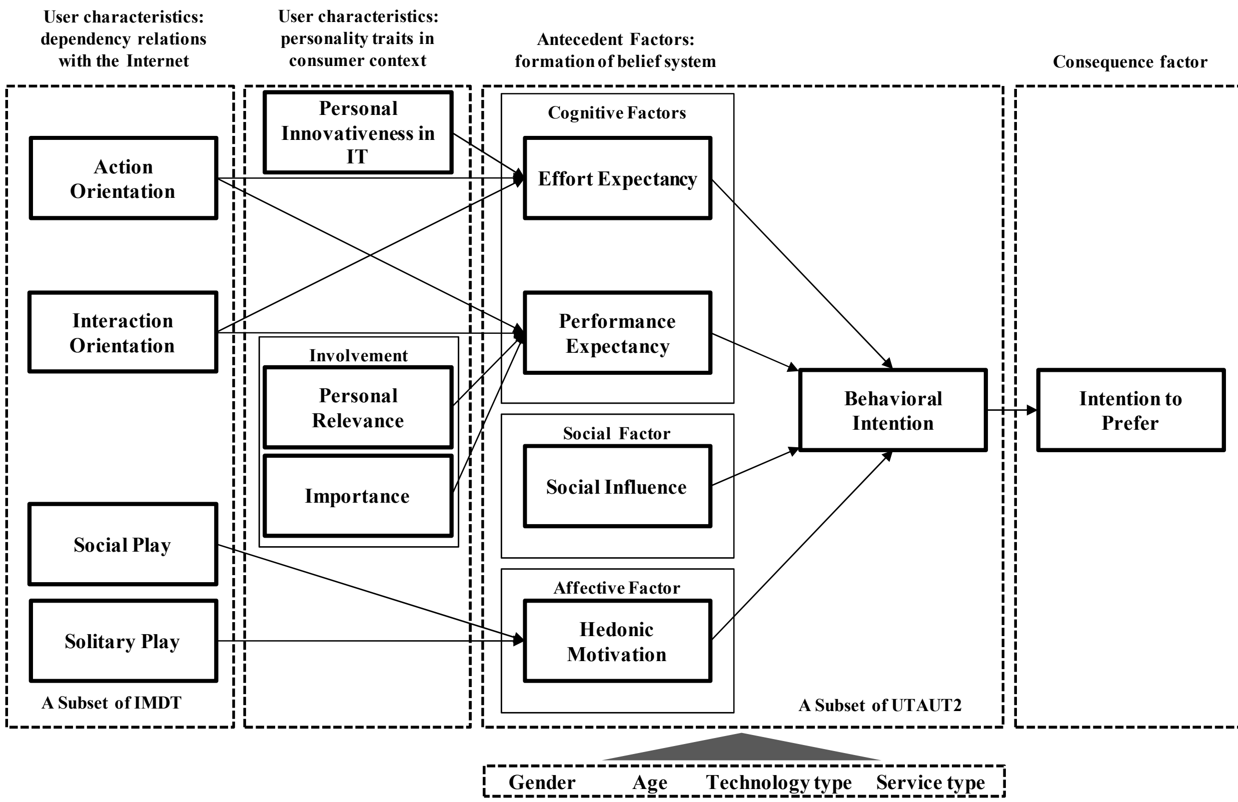


Figure 24: The final conceptual model of this dissertation

5 Empirical Study

After developing the conceptual model for the acceptance of in-store ubiquitous computing-based information services, the purpose of this chapter is to empirically examine the model. The first step in conducting an empirical study is to cautiously select a statistical analysis method. Therefore, next, the suitability of different statistical methods to the objectives and characteristics of the current research is discussed and PLS-SEM is chosen as the most appropriate statistical method for the empirical analysis of this dissertation. After constructing the structural and measurement models, a data set has been collected by conducting a scenario-based online survey. Lastly, the quality of PLS estimates engendered from the data set are assessed and their implications for the hypothesized relationships are discussed.

5.1 Selecting the Statistical Analysis Method

Hair et al. (2010) provide researchers with a classification of multivariate analysis methods and a corresponding clear-cut procedure to select the most appropriate analysis method. As shown in Figure 25, the procedure to determine the appropriate multivariate analysis method starts by answering the straightforward question of *"what types of relationships [between the variables] are being examined"* (Hair et al., 2010, p. 12). Due to the fact that in this dissertation, the relationships between more than two variables will be investigated, univariate analysis (analysis to examine the distribution of a single variable) and bivariate analysis (analysis to examine the relationship between two variables) are subsequently excluded.

Following the recommended procedure by Hair et al. (2010) to choose the appropriate analysis method, first the nature of the relationships under study needs to be examined; being it the relationship between dependent and independent variables or the structure of the relationship, different statistical analysis methods should be applied. In the theoretical model of this dissertation, there are multiple relationships between several dependent and independent variables. Therefore for this dissertation only multivariate dependence methods are applicable (see the left branch in Figure 25) as opposed to interdependence methods (the right branch of Figure 25).

The next step is to decide which dependence method is the most appropriate one for the purpose of the study. This decision can be made by answering the question *"how many variables are treated as dependent in a single analysis"*(Hair et al., 2010, p. 11); if the goal is a simultaneous estimation of the relationships between multiple dependent and independent variables, as is the case in this study, then structural equation modeling is the most appropriate method. Otherwise multivariate analysis of variance or multiple regressions would be a better fit (Hair et al., 2010). To sum up, for simultaneous estimation of complex, causal relationships, structural equation modeling is the best fitting method (Chin, 1998a).

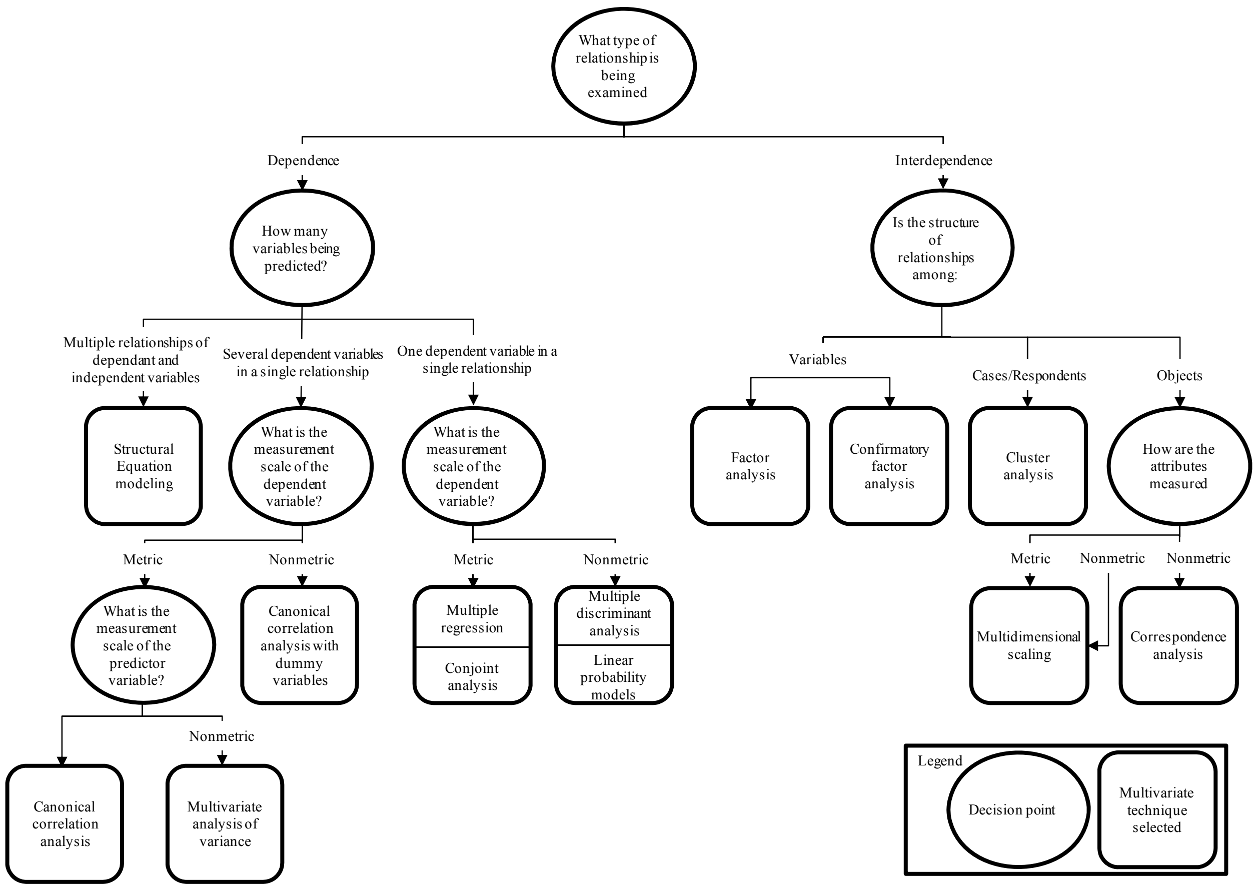


Figure 25: Selecting a multivariate technique (Hair et al., 2010, pp. 12–13)

Furthermore there are two additional motives to apply structural equation modeling, namely the possibility to define relationships between latent variables and the ability to reduce the measurement errors (Hair et al., 2010). Latent variables are "*hypothetical constructs invented by a scientist for the purpose of understanding a research area*" (Bentler, 1980, p. 420) which cannot be observed or directly measured (Borsboom et al., 2003). Structural equation modeling allow the analysis of relationships between latent variables through the integration of regression and factor analysis methods (L. J. Williams et al., 2009). These theoretical constructs can be estimated through so-called measurement models consisting of indicator variables which can be empirically collected and tested (Rigdon, 1998). Hence, structural equation modeling enables the measurement of latent variables and thus estimation of causal relationship between latent variables. In addition, the potential measurement error, rooted in the very nature of the empirical data collection, can be reduced by the inclusion of several indicator variables to measure a single latent construct which also leads to better statistical estimates of existing relationships with other latent variables (Hair et al., 2010).

Considering the reasons mentioned above, structural equation modeling has been chosen as the most appropriate method to fulfill the objectives of this dissertation. The following two sections (5.1.1 and 5.1.2) are devoted to the review of the structural equation modeling technique, its types, their strengths and weaknesses and the type of studies for which they are most suitable. The goal of this review is guiding the decision of which structural equation technique fits the best to the objectives of the current dissertation.

5.1.1 Structural Equation Modeling

The term, structural equation modeling, refers to a group of multivariate statistical methods used for empirical examination of theoretically derived statements about complex relationships between multiple variables (Chin, 1998b; Rigdon, 1998; Ringle, 2004a; Hair et al., 2010; Kline, 2011). In 1904, Spearman (1904) developed the exploratory factor analysis, a few years prior to the introduction of path analysis by a biogeneticist, Wright (1918). Years later, during the 1970s, a framework named the JKW model (Bentler, 1980) was developed. It was named as such in reference to its three authors: Jöreskog, Keesling, and Wiley; the JKW model integrated the factor analysis (measurement approach) and the path analysis (structural approach) bringing about what became the basis for what is now known as the structural equation modeling (Kline, 2011). Thus, structural equation modeling is also referred as the second generation statistical methods as it integrates the first generation methods namely regression and factor analysis (Fornell and Larcker, 1987; Hair et al., 2012a, 2014a). Thanks to the significant theoretical and methodological contribution of Jöreskog and Sörbom (Jöreskog, 1970; Jöreskog and Van Thillo, 1972; Jöreskog et al., 1979; Jöreskog and Sörbom, 1982) as well as the introduction of the first software program for its analysis, dubbed LISREL, today the application of the structural equation modeling has noticeably increased making it a quasi-standard approach in the social and economic sciences (Wold, 1980; Bollen, 1989; Chin, 1998b; Hair et al., 2011, 2012b).

As mentioned earlier, using structural equation modeling, it is possible to examine theoretically derived relationships between latent constructs. To be able to collect empirical data for these not directly measurable latent constructs, it is necessary to assign a measurement model to each of them consisting of a single or a group of indicator variables. These indicator variables, which are derived from theory and thus are strongly connected to the latent construct, can be then measured empirically (Rigdon, 1998); so that, the relationships between the latent variables can be analyzed based on the variances and covariances of the empirically collected indicator variables.

The development of the structural equation modeling was accompanied by the development of a modeling language which enables the presentation of a structural equation model in a path diagram (Loehlin, 2004), commonly referred to as a path model. A path model is a diagram made by the researcher when using a structural equation method to translate the research hypotheses into a simply absorbable illustration of variables and relationships (Hair et al., 2014a). The reason for making a path model early during the research is to offer the researcher a better view of the problem and additionally facilitate the collective work of a group of researchers on the same project (Hair et al., 2009). Figure 26 is a path model of an exemplary structural equation model, demonstrating the relationships between latent variables (paths), commonly referred to as structural model, as well as relationships between each latent construct and its associated indicators, commonly referred to as measurement model. This structural equation model is divided into a structural model and two measurement models. The structural model consists of five latent variables, $Y_{1,\ 2,\ 3}$ and $Y_{4,\ 5}$ which are respectively called exogenous (that explain the other latent constructs, thus are independent) and endogenous (that are explained by other latent constructs, thus are dependent). External influences on endogenous variables that cannot be theoretically explained are called residual variance or error term (Bollen, 1989; Hair et al., 2014a). For example, in Figure 26, the endogenous variable Y_4 is explained by exogenous variables $Y_{1,\ 2}$ as well as the error term z_4. The path coefficients p_{14}, p_{24}, p_{25}, p_{35}

describe the direct relationships between the exogenous and endogenous variables, while the path coefficient p_{45} represents the relationship between the endogenous variables.

As previously mentioned, for each latent construct, a measurement model is assigned which consists of one or more indicators, also referred to as items or manifest variables. In Figure 26, measurement models for endogenous and exogenous variables are illustrated on the right and left side of the structural model. These directly measurable indicators that are theoretically connected to their corresponding latent constructs shape the estimates of the structural relationships between the latent constructs.

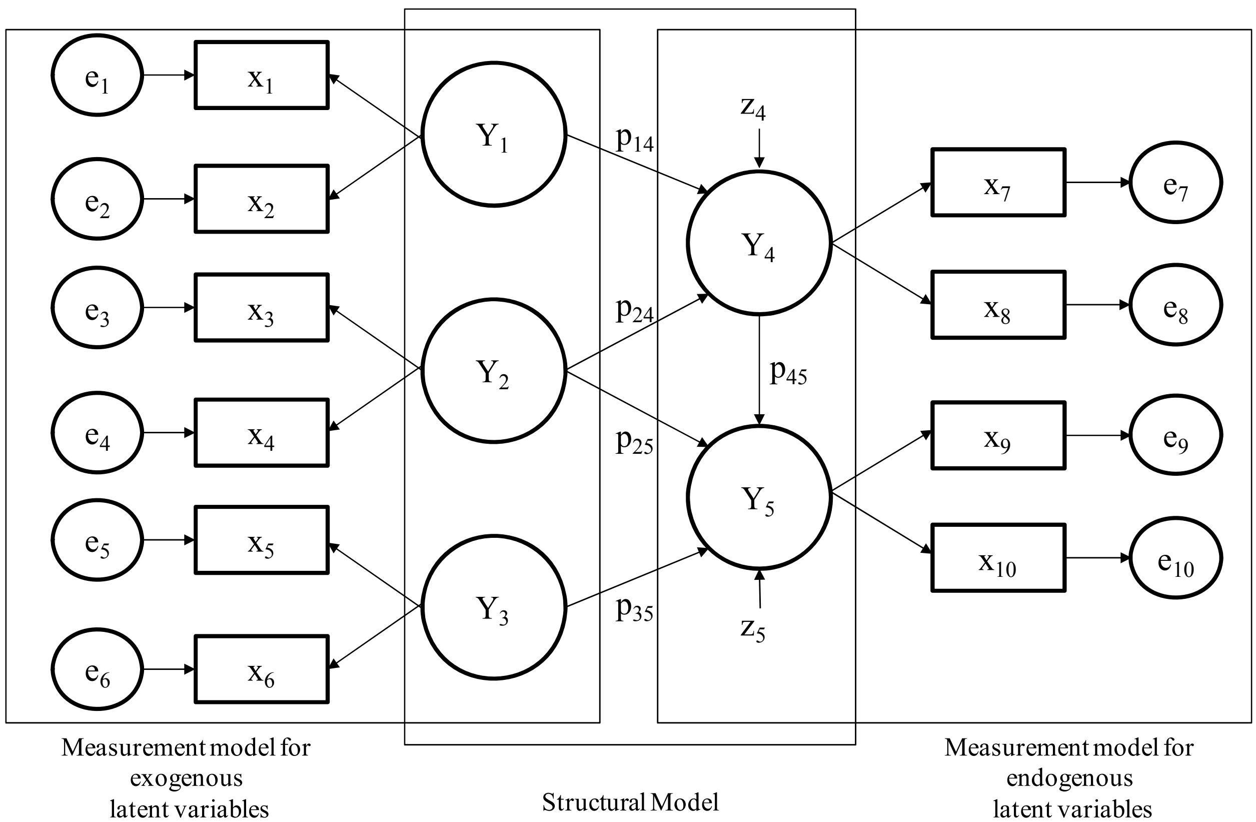


Figure 26: Graphical presentation of an exemplary structural equation model

After having the model ready, to obtain the results for the relationships in the structural equation model, next, the structural and measurement model parameters should be estimated. For this purpose, two major statistical approaches are available, the covariance-based technique (CB-SEM) (Jöreskog, 1978, 1993) and variance-based partial least squares technique (PLS-SEM) (Wold, 1966; Lohmöller, 1989) (Ringle, 2004b; Hair et al., 2012b, 2014a).

Since 1970s the covariance-based structural modeling has found a prominent place in practice and research. The partial least squares approach was developed by Wold (1975) during the 1970s as a successor to non-linear iterative least squares (NILES) and non-linear iterative partial least squares (NIPALS) (Jöreskog and Wold, 1982). However, unlike covariance-based structural modeling, there was a late emergence of software programs utilizing the PLS-SEM algorithm (Hair et al., 2011, p. 140) such as PLS-Graph (Chin, 2001) or SmartPLS (Ringle et al., 2005).

For Wold, the goal from establishing PLS-SEM was to have an alternative to CB-SEM; one that had a better disposition towards prediction and more important, one that dealt with the rigidity in the data requirements (e.g. the normality of the data and minimum sample size required) and the rigidity in the specification of relationships (Hair et al., 2014a; Tenenhaus et al., 2005). Today, there is a consensus among academia that PLS-SEM has, indeed, delivered on both counts. Consequently, the number of publications featuring PLS-SEM has increased over the years and it has become a reflex to many researchers to strongly consider this approach when dealing with relationships between latent variables.

Although both CB-SEM and PLS-SEM approaches share the fundamentals of structural equation modeling, there are still principal differences between them (Hair et al., 2012b; Jöreskog and Wold, 1982; Rigdon et al., 2017). Typically, researchers are guided by the objective of their research when choosing either approach. In this regard Ridgon et al. (2017, p. 11) note that "*there is not the single best option as the choice of a method depends on the explicit and implicit assumptions a researcher makes regarding the phenomena under study and our ability to measure them comprehensively*". Thus before applying a structural equation modeling method, one should consider the pros and cons of each depending on the research question (Hair et al., 2014a; Ringle et al., 2012).

The following section is dedicated to the comparison of both methods in contemplation of identifying the most appropriate method for the analysis of the present work. It is important to note that this section does not aim to offer a detailed description of the exact mathematical processes of each approach but it will rather compare the principle functions, underlying assumptions and restrictions of each method to finally answer the question of which method is the most appropriate for this work.

5.1.2 PLS-SEM and CB-SEM

To answer the question of which structural equation modeling is the most appropriate method for this research, the characteristics and objectives of each methodology should be considered along with the nature of the question under research (Hair et al., 2014a). There is an ample support to the claim that each of the two approaches is stronger than the other, contingent on the aim of the research (Fornell and Bookstein, 1982; Hair et al., 2011, 2014a; Henseler et al., 2009; Marcoulides et al., 2009; Ringle et al., 2012; Sarstedt et al., 2017; Rigdon et al., 2017). Detailed guidelines can be found in the literature concerning the use of each approach. Thus, below there will be no exhaustive review of literature in the field but simply a selective review of all criteria relevant to the determination of the SEM approach that is most appropriate for the current work.

Differences between CB-SEM and PLS-SEM are mainly rooted in the differences in their estimation procedure which in turn causes differences in the requirements for the data characteristics, the theoretical model and consequently model evaluation results. The first step in making the choice between CB-SEM and PLS-SEM is to clearly determine the research objective.

A closer look at the estimation algorithms of CB-SEM and PLS-SEM reveals why researchers need to determine their goal as a first step in choosing the analysis method. While the CB-SEM uses a maximum likelihood estimation method, in the PLS-SEM, ordinary least squares (OLS) regression-based method is used. The modus operandi in the CB-SEM approach is that a covariance matrix is computed based on the sample dataset. Later on, calculations of parameters' estimates are made. These estimates permit minimizing a fitting function defined as the difference between the correlations implied by the parameter estimates and the sample correlation (Anderson and Gerbing, 1988; Hair et al., 2011; Kline, 2011), this is done in an iterative manner and only stops when there is no improvement possible. In other words CB-SEM tries to maximize the fit of a model-based covariance matrix to the data-based covariance matrix allowing the assessment of how well a theoretical model fits the observations (Chin, 1998b; Lohmöller, 1989). This approach provides optimal estimations for the model parameters however it does not permit to predict observed indicators.

On the other hand, PLS-SEM algorithm is mainly a sequence of ordinary least squares regressions in terms of weight vectors. The resulting weight vectors satisfy fixed point equations at convergence level which is obtained when outer weights between two iterations fall below a fixed threshold (Hair et al., 2011, 2014a; Henseler, 2010; Henseler et al., 2009; Marcoulides et al., 2009). Through the OLS approach, the aim is to minimize the error terms and residual variances of endogenous variables thus maximizing the explained variance (also known as predictive), R^2, of the total variance of a construct. This enables the most accurate prediction of endogenous latent variables (Hair et al., 2014a, 2014b; Sarstedt et al., 2014; Urbach and Ahlemann, 2010). For that reason PLS-SEM is particularly appropriate when the research objective is prediction of influencing factors of a certain construct (Chin and Newsted, 1999a; Hair et al., 2014a; Ringle et al., 2012; Sarstedt et al., 2014; Urbach and Ahlemann, 2010). The superiority of PLS-SEM in predictive capabilities is also backed by various simulation studies (Becker et al., 2013; Evermann and Tate, 2016; Sarstedt et al., 2017). In addition PLS-SEM holds a higher statistical power making it particularly suitable for exploratory research setting and development of new theories (Sarstedt et al., 2017).

Another important criterion for the choice of CB-SEM or PLS-SEM is the characteristics of the data of the empirical study and the model complexity (Chin and Newsted, 1999a; Sarstedt et al., 2017; Urbach and Ahlemann, 2010). The PLS-SEM is more appropriate when dealing with small sample sizes (Reinartz et al., 2009). The statistical properties of the PLS-SEM, that is estimation of the structural model's partial regression relationships instead of simultaneous calculations of all relationships, allow robust estimation results for small sample sizes even for complex models with a large number of latent variables (Hair et al., 2014a; Hui and Wold, 1982; Sarstedt et al., 2017).

Mapping the advantages and constraints of each method on the requirements of the empirical analysis of this work, overall, the research objectives, the empirical data characteristics, and model complexity are in favor of using PLS-SEM. The aim of this work is to identify the relevant antecedent constructs of the intention to use and intention to prefer of in-store ubiquitous computing-based information services. Here, one of the objectives is the assessment of the potential effect of Internet information dependency on the intention to use determinants of technology acceptance theory. Firstly, it is important to note that, acceptance studies in the field of in-store ubiquitous technologies are not yet mature. Furthermore, there is no previous study in this field incorporating media dependency theory into technology acceptance theory. Under these circumstances, the developed conceptual model of this study cannot be considered as a well-established theory; thus the focus here is on a high explanatory power of individual relationships. Consequently, this study falls under the category of exploratory research and theory development, hence making PLS-SEM the more appropriate choice.

In addition, in line with the objectives of this work, the analyses are also aimed to serve as foundation for the follow-up recommendations on course of actions to support brick and mortar retailers in development and implementation of the ubiquitous computing based information services; to do so an importance-performance matrix analysis (IPMA) will be conducted. For this, the latent variables scores which are generated within the framework of PLS-SEM parameter estimation are required (Völckner et al., 2010). Besides, in agreement with UTAUT2, the effects of demographic factors of age and gender on relationships between the determinants and intention to use are included in the theoretical foundation. For empirical study, this means the division of the total sample size into several subgroups in order to perform multi-group analysis. Evidently, the divided sample sizes result in smaller sub-sample sizes, in the case of the current study it lies partly below 150 observations; again making it more judicious to apply PLS-SEM (Hair et al., 2014a; Sarstedt et al., 2017). Having chosen PLS-SEM for the analyses of this work, following section is dedicated to the application procedure of this method.

5.2 PLS-SEM Analyses

Having discussed the structural equation modeling and the choice of PLS-SEM, the rest of this chapter is dedicated to application procedure of PLS-SEM for the analyses objectives of this dissertation. Figure 27 is an illustration of the typical stages for the application of the PLS-SEM accompanied with the corresponding steps adapted to the objectives and characteristics of this dissertation. The whole process can be divided into four different phases, namely creation of the structural and measurement models, estimation of the models, and assessment of the results and finally interpretation of the results. The very first step here is the construction of the structural model based on the theoretically derived hypotheses. As mentioned in section 5.1.1, the latent variables constructing the structural model are not directly observable; therefore in the second stage, a measurement model should be developed for each latent construct which consists of observable indicators. In the third stage, the measurement model will be used to build a questionnaire for the empirical data collection and examination. After collecting the data, the PLS-SEM model results can be estimated which delivers the empirical values for measurement as well as structural models (Hair et al., 2014a). Having the results of analyses, in the subsequent fifth and sixth stage, the quality of the results should be evaluated to examine the extent to which the theoretical measurement and structural models match the data (Hair et al., 2014a). The last stage of the process is typically representing the interpretation of the results along with their implications for research and practice.

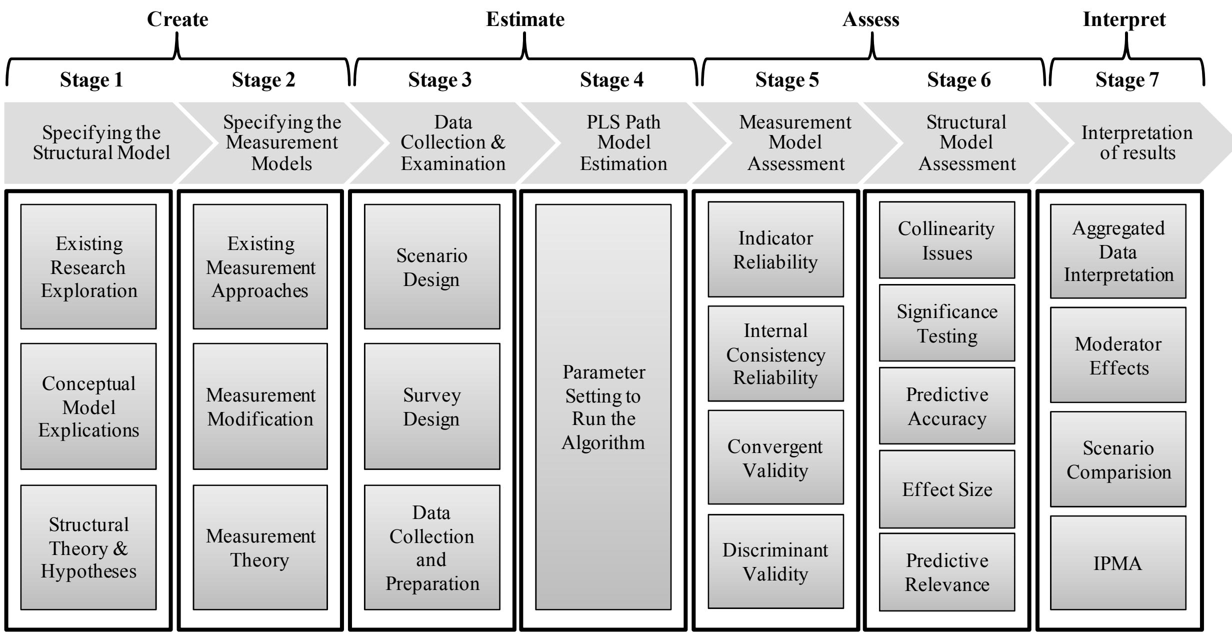


Figure 27: Procedure of applying PLS-SEM for this work based on the stages from Hair et al. (2014a)

5.2.1 Model Creation

The very first step here is the construction of the structural model based on the theoretically derived hypotheses. As mentioned in the section 5.1.1, the latent variables involved in the structural model are not directly observable; therefore, as second stage, a measurement model should be developed for each latent construct which consists of observable indicators.

To be able to test the developed hypotheses in acceptance of the in-store ubiquitous computing-based information services applying the PLS-SEM, first, all hypothesized relationships should be translated into a path diagram. Figure 28 shows the path diagram of this dissertation derived from the developed conceptual model.

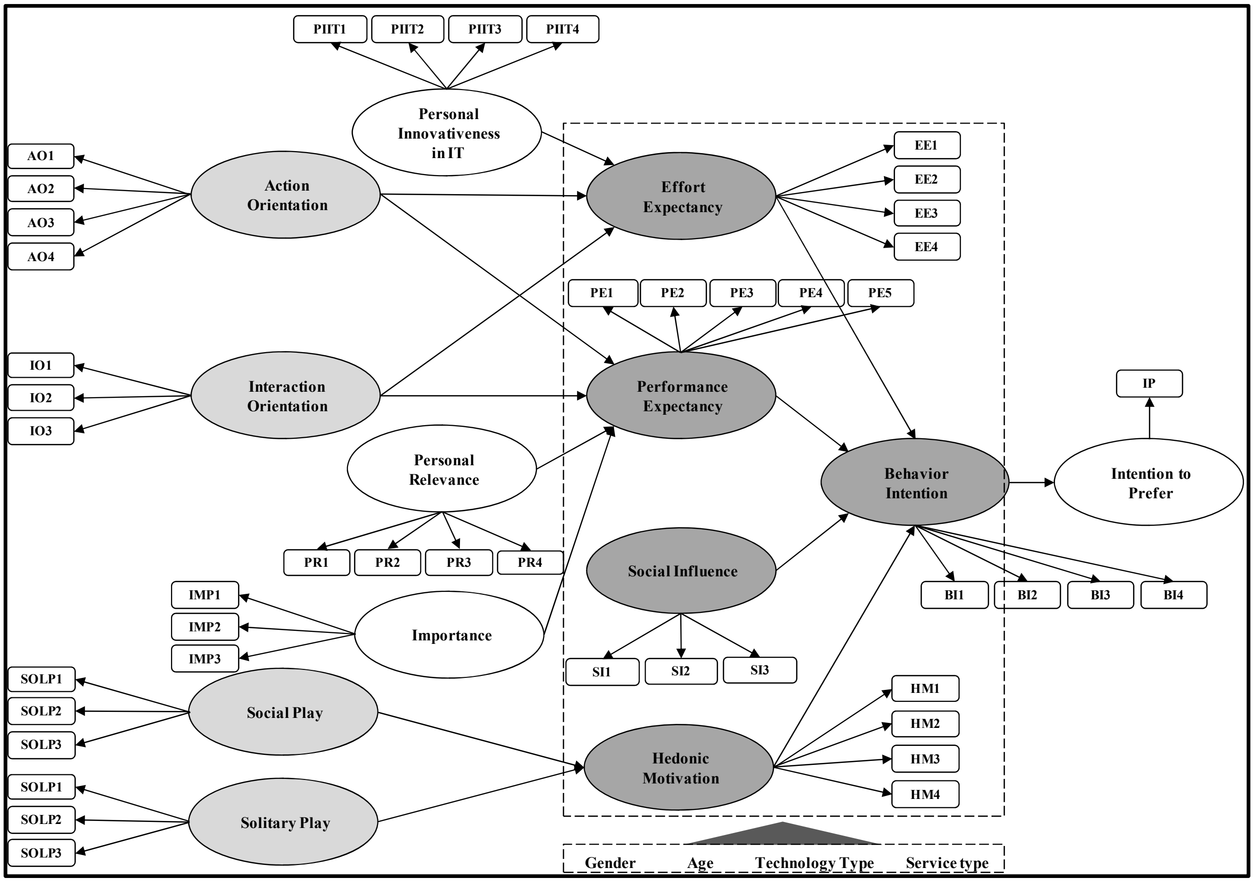


Figure 28: Path diagram for the acceptance model of in-store ubiquitous computing-based information services

After specifying the structural model for acceptance of in-store ubiquitous computing based information services, the next step in model creation is development of the measurement theory. The objective here is establishing a theoretically grounded measurement instrument to make the latent constructs of the model measurable, thus enabling the empirical data collection for the analyses. For this purpose, for each latent construct a measurement model should be assigned, which may consist of one or more indicators. As shown in Figure 27, this stage is made of three steps, namely exploring the existing measurement approaches, modification and adjustment of the existing measurement instruments to the research context and finally development of a measurement instrument.

As discussed thoroughly in chapter 4, the conceptual framework of this dissertation consists of four distinct sets of constructs, namely antecedent factors of behavior intention (based on UTAUT2), a consequence factor of behavior intention, and relevant user characteristics in the technology and consumer context as external contextual factors along with user's Internet dependency relations (based on IMD theory) as external contextual factors. For each set of constructs, the existing measurement instruments have been explored and the ones which have been extensively validated in the literature were selected. In the next step the selected measurement instruments were adjusted to the context of this dissertation. The remainder of this section is dedicated to the elaboration of this process for each set of constructs.

The measurement instruments for the UTAUT2 constructs were developed based on the original UTAUT constructs. For each, the original items were reexamined, screened and adapted (mostly rephrased) to the context of the present study. Table 17 lists the indicators of UTAUT2 constructs for this study.

Table 17: Indicators of UTAUT2 constructs in acceptance model of in-store ubiquitous computing based information services

Construct (latent variable)	Indicator code	Indicators
Behavioral Intention (BI)	BI1	I would like to shop in stores which have such technologies.
	BI2	I would use this technology frequently.
	BI3	I wish this technology was already available.
	BI4	I intend to use the presented technology if available.
Performance Expectancy (PE)	PE1	I think using the presented technology will help me find what I want faster and easier in the shop.
	PE2	The presented technology will make shopping more convenient for me.
	PE3	Overall, I think the presented technology will be useful for me.
	PE4	The presented technology will improve my shopping experience
	PE5	The presented technology will fit with my shopping needs.
Effort Expectancy (EE)	EE1	Learning how to use the presented technology seems easy for me.
	EE2	I think my interaction with this technology would be clear and understandable.
	EE3	The presented technology appears to be easy to use.

	EE4	It would be easy for me to become skillful at using the presented technology.
Hedonic Motivation (HM)	HM1	The presented technology will make the shopping more fun for me.
	HM2	I will enjoy shopping more in shops with this technology.
	HM3	The presented technology will make the shopping very entertaining.
	HM4	The presented technology would feel like playing a game for me.
Social Influence (SI)	SI1	My friends and/or family would be impressed to hear that I use this technology.
	SI2	My friends and/or family would be interested to use this technology.
	SI3	I think most people in my community will use the presented technology for shopping.

Construct items related to the IMD theory were as well developed based on the original IMD measurement tools. IMD theory consists of six different levels of dependency relations between an individual and a media system. Each of these levels covers a specific goal (Understanding, Orientation or Play) and is either targeting the persons themselves or their social environment (see section 3.2.2). With only four dimensions selected as relevant, in this research the total number of IMD measurement tools implemented is thirteen items. Items for each of the mentioned variables were adopted and embedded directly from the literature with no changes made in phrases except for action orientation where the items had to be adapted to the context of the research. Table 18 lists the indicators of IMD constructs for this study.

Table 18: Indicators of Internet dependency constructs in acceptance model of in-store ubiquitous computing-based information services

Construct (latent variable)	Indicator code	Indicators
Action Orientation (AO)	AO1	Internet helps you to decide where to buy certain products/services.
	AO2	Internet helps you to decide what to buy.
	AO3	Internet helps you to decide between alternative products/services.
	AO4	Internet helps you to decide whether to buy a certain product/service or not.
Interaction Orientation (IO)	IO1	Internet helps you to discover better way to communicate with others.
	IO2	Internet helps you to think about how to act with friends, relatives, or people you work with.

	IO3	Internet helps you to get ideas about how to approach others in important or difficult situations.
Solitary Play (SOLP)	SOLP1	Internet helps you to stop thinking about work and problems after a hard day or week.
	SOLP2	Internet helps you to relax when you are by yourself.
	SOLP3	Internet helps you to have something to do when nobody is around.
Social Play (SOCP)	SOCP1	Internet gives you something to do with your friends.
	SOCP2	Internet helps you to have fun with family or friends.
	SOCP 3	Internet helps you to be a part of events you enjoy without having to be there.

In addition to UTAUT2 and IMD constructs, few additional variables that are not part of the two theories is integrated in the research model namely intention to prefer, personal innovativeness in information technology, importance and personal relevance. Intention to prefer is a unique instrument construct; it measures the respondents' intention to prefer a shop where the technology is available over an ordinary store. The item for the this construct was developed based on Intention to Prefer from Kowatsch et al. (2011) shown in Table 19.

Table 19: Indicator of the consequence construct of acceptance in acceptance model of in-store ubiquitous computing based information services

Construct (latent variable)	Indicator code	Indicators	Adopted from
Intention to Prefer (IP)	IP	I would prefer a retail store where the presented technology is available to use over an ordinary store.	(Kowatsch et al., 2011)

The construct of personal innovativeness has a long tradition in innovation acceptance research. The traditional approach to measure the personal innovativeness however is rather a posteriori approach. That is measuring the innovativeness of a user after that she has taken the decision of using an innovation. Such an approach doesn't support an a priori identification of innovative users (Goldsmith et al., 1998). As a response to this limitation, a variety of measurement approaches have been introduced in the literature for a direct measurement of personal innovativeness for an overview see (Agarwal and Prasad, 1998). Among them the scale developed by Goldsmith and Hofacker (1991) has found a widespread acceptance. Goldsmith and Hofacker (1991) proposed a domain specific innovativeness (DSI) scale to measure the tendency of individuals to be among the first customers to try the new products in a particular category. The DSI consists of six indicators based on personal opinions and behaviors. Various studies report a relatively high reliability and validity of the DSI (Agarwal and Prasad, 1998; Bearden et al., 2011; Goldsmith et al., 1998; Pagani, 2007; Roehrich, 2004). Applying the scale of Goldsmith and Hofacker (1991) to the domain of information technology, Agarwal and Prasad (1998) developed a new scale titled as personal innovativeness in the information technology. The scale consists of four prototypical statements on the use of Information technologies, which in the original work was measured using a seven-point scale. In this dissertation, the scale from Agarwal and Prasad (1998) is used as the basis for the formulation of indicators of personal innovativeness. Three general statements concerning individuals' tendency to use information technology have been formulated as indicators. Finally the indicators for importance and personal relevance constructs have been derived from the work of Mayer (2012). Table 20 lists the indicators for these constructs. The measurement models for all of the latent variables are graphically presented in Figure 28.

Table 20: Indicators of user characteristic constructs in acceptance model of in-store ubiquitous computing-based information services

Construct (latent variable)	Indicator code	Indicators	Adopted from
Personal Innovativeness in IT (PIIT)	PIIT1	I like to experience products that use new technologies.	(Agarwal and Prasad, 1998)
	PIIT2	Among my peers, I am usually the first to explore new information technologies.	(Agarwal and Prasad, 1998)
	PIIT3	I feel comfortable using new information technologies.	(Agarwal and Prasad, 1998)
	PIIT4	In general, I am hesitant to try out new information technologies.	(Agarwal and Prasad, 1998)
Importance (IMP)	IMP1	I often have trouble choosing which item to buy when I am shopping.	(Mayer, 2012)
	IMP2	I often end up buying something that I don't need, because I get confused when I am shopping.	(Mayer, 2012)
	IMP3	I would like to have some assistance when I am shopping, especially when the product I need is expensive.	(Mayer, 2012)
Personal Relevance (PR)	PR1	It is important to me to feel like a smart shopper and to make successful purchases.	(Rintamäki et al., 2006b)

			(Mayer, 2012)
	PR2	It is important to me that the products I buy are consistent with my style.	(Rintamäki et al., 2006b) (Mayer, 2012)
	PR3	It is important for me to inform myself about the alternatives (e.g., price, quality) before making the purchase.	(Mayer, 2012)
	PR4	When I am shopping, I am usually very careful with the decisions I make.	(Rintamäki et al., 2006b)

5.2.2 Data Collection and Examination

The second phase of application procedure of PLS-SEM is the estimation of the results. After creating the structural and measurement model, to be able to run the PLS-SEM algorithm to estimate the results, a data set for indicator variables of the model should be collected and prepared. Therefore, next, first the data collection procedure and the characteristics of the collected data will be discussed. To investigate the research questions and hypotheses of this work, a scenario based survey method has been chosen.

Scenario Development

Application of scenario based surveys is quite common in technology acceptance research (Kokkinou and Cranage, 2011); scenarios as research stimuli are especially employed when innovations or new technologies are not existent or very rare in the market, but early customer acceptance and requirements are to be explored (Cheng and Yeh, 2011; Lancelot Miltgen et al., 2013; Rothensee, 2010). Therefore, using scenarios while empirically studying the acceptance of ubiquitous computing systems has turned to be a common practice (Kaasinen et al., 2012; Lancelot Miltgen et al., 2013; Lanseng and Andreassen, 2007; Mayer, 2012; Okazaki and Mendez, n.d.; Olsson, 2012; Rothensee, 2010; Roussos and Moussouri, 2004). To conduct a scenario based survey, formulated scenarios are presented to the subjects of the study as a stimulus to make an acceptance decision. Scenarios in this context are short stories about an incident in which a user is performing an act or a sequence of activities with a new technical system (Carroll, 2000). They are used in order to visualize innovative technologies and to make them tangible to customers (Carroll, 2000). A scenario includes description of the setting, agents or actors, objectives, actions and events as well as the impact of actions and events on the goals (Carroll, 2000).

The advantages of this survey method lie in its simple and inexpensive design and implementation. In addition, the method enables the early acceptance assessment of the future technologies. The challenge is however to design a scenario which can induce a uniform conception about a given technology among all participants. Especially considering that people differ in their abilities to put themselves in a hypothetical situation.

In this work scenarios are used to make in-store ubiquitous computing based information services understandable to the users in order to carry out a corresponding questionnaire. Three objectives of this dissertation are of special importance while developing the required scenarios:

- Empirical exploration of the developed theoretical model for user acceptance of in-store ubiquitous computing-based information services
- Empirical exploration of theoretical model for different service types (services for information search vs. alternative evaluation) in order to identify the stage specific determinants of user acceptance
- Empirical exploration of the theoretical model for different technology categories (store owned vs. user-owned), in order to identify the potential system specific determinants of user acceptance

Considering these objectives, three comprehensive technology-enabled retail scenarios that include a number of realistic ubiquitous computing-based services to support information search process of the customers in traditional retail environment is developed. First, to be able to empirically explore the theoretical model for information search and alternative evaluation, two distinct scenarios for a store based technology are developed each encompassing technology based services supporting customers in the given stage. For empirical exploration of the theoretical model for both store-based and mobile applications, one additional scenario for services offered on users own mobile device is formulated. In addition, having different scenarios for distinct service and technology types enables to collect a more valid aggregated dataset.

To ensure the relevance and feasibility of the scenarios, the technology and the services illustrated in the scenarios are chosen based on the literature, industrial reports, and real applications of in-store ubiquitous computing technologies which have been thoroughly discussed in section 2.2. The first and second scenarios are dedicated to store-based stationary system (smart mirror). Whereas the first scenario focuses on information search stage, the second one is about alternative evaluation stage, enabling the comparison of the empirical results among the stages. The third scenario is dedicated to applications on customers own mobile devices so that comparison of the empirical results between this scenario and the first scenario can enable the exploration of the theoretical model for different technology types.

The formulation of the scenarios is kept clear and simple. All scenarios include a description the usage environment, the person involved, the objectives and activities as well as the types of assistance and the interaction with the system. To reduce the product bias, that means if a person finds the product in a scenario not attractive or irrelevant it can affect her perception about the technology based services, the opening paragraphs for scenario one and three are formulated to stimulate the need to buy the product. To decrease the risk of the inconsistent conception of the scenarios among participants, all scenarios are augmented by various pictures made in Photoshop. In addition to make it easier for the participants to put themselves in the scenario context, for each scenario a male and female version is formulated.

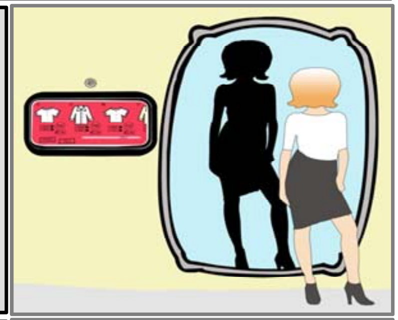
After developing the first drafts of the scenarios for the purpose of evaluation, the scenarios were presented and discussed during a workshop. Nine peers attended the workshop for 120 minutes. In a presentation, the attendants were briefed about the purpose of the research, purpose of the workshop, the procedure as well as the evaluation criteria as:

- Wording and clarity of scenarios and questions (considering that the English scenarios are designed for German audience)
- The consistency of the text and the pictures in the scenarios
- The layout design of the scenarios (e.g. the alignments of the text and pictures)
- Picture features (e.g. clarity, size in the text, color)
- The suitability of the length and the number of scenarios (e.g. too many, too few scenarios to cover the topic)

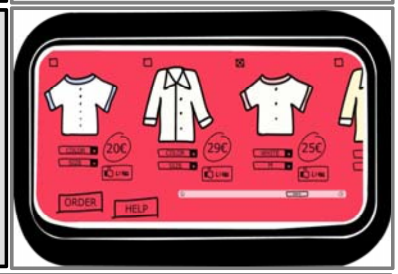
The scenarios were revised based on the comments and recommendations received from peers. Then the edited scenarios were sent to two different evaluators with the request for written comments. Again the scenarios were revised based on the evaluators' comments. The final scenarios for female participants are shown in Figure 29 and Figure 30.

Scenario 1- Smart Mirror (Information Search)_Female

Lisa enters the floor dedicated for women clothing in a large department store. She needs an outfit for her upcoming job interview. Therefore she is looking for a white blouse and a dark skirt. The floor is huge and full of different brands with different styles. She looks for a shop assistant to get some advice concerning where to find the business outfits, but all shop assistants seem to be busy at the moment. So she picks two blouses and a skirt and takes them into the fitting room. The skirt fits very well, but none of the blouses suit her taste.
She uses the Smart Mirror in the cabin for inspiration on blouses that could fit well to the skirt and are available in the store: Pressing a button, Lisa activates the Smart Mirror function; the Smart Mirror scans Lisa's body.



Now Lisa interacts with the Smart Mirror and it proposes a list of blouses which could fit well to the skirt on a small screen located next to the Smart Mirror, based on the occasion (formal outfit/interview outfit) and her age and size. She has the option to filter the given list based on different criteria (size, color, brand, on sale etc). She filters the options based on price (less than 30 Euro) and color (white). Then, she browses the options and chooses five blouses to try on. She orders her favorite ones via touch screen and a shop attendant delivers them to her.



Scenario 2- Smart Mirror (Alternative Evaluation)_Female

After trying on the five blouses she has ordered via touch screen to the fitting room, Lisa has three white blouses in her consideration set. She wants to buy just one. She has never bought from these brands and doesn't know the quality.

Given that she is quite sensitive about the Price-Performance ratio (Preis-Leistungs-Verhältnis) of any product she buys, she interacts with the Smart Mirror again. While trying on each blouse, she touches the blouse on the Mirror and the details of the product as well as reviews on the products from other customers appear in an information box in the corner of the Mirror. She chooses the one with the best review and buys the white shirt and the skirt. Being confident of his choices, she is looking forward to convince her new boss in the upcoming job interview.

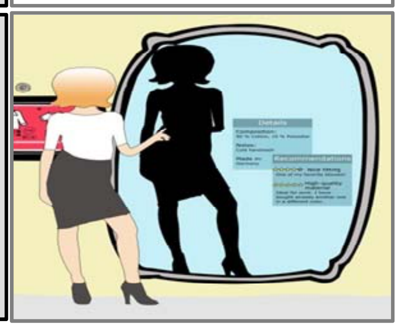


Figure 29: Smart Mirror scenarios for information search and alternative evaluation stages

Scenario 3- Mobile Applications (Information Search)_Female

Julia studies at Hamburg University of Technology. In a gathering after a course, Julia's friends are speaking about the advantages of Tablets (Tablet Computers) for their studies. One friend says that she could load all her lecture materials on it to read while sitting in the train, the other is fascinated with the possibility to find additional information she might need through the internet and the other one uses her Tablet to write comments and notes directly in the documents while sitting in the train or during the lectures. Being convinced of the advantages, Julia decides to purchase a Tablet. Few days later, she enters a very large electronics store and heads to the tablet section. She goes through the assortment of Tablets in the store. Soon she finds a Tablet which suites her taste. The design is very nice and it has all the features she desires, but unfortunately it is too expensive. She uses her Smartphone to open the App. of the store to find out if there is a similar (with the same main functions) but a cheaper product. She scans the barcode of the Tablet she likes and it appears on her phone. Then she chooses the category "Similar Products" and filters all the functions she would like her new Tablet to have.

Three different Tablets fit her requirements and show up on her screen. She is able to directly compare all the features: price, brand, technical features (front camera, rear camera, expandable storage, etc) presented in an easy to compare matrix. By clicking on each option, she has the possibility to look for more detailed information of every Tablet in particular. Julia always needs some time to think about a bigger spending. She saves the search options in her "Dream Box" to get to see them later.

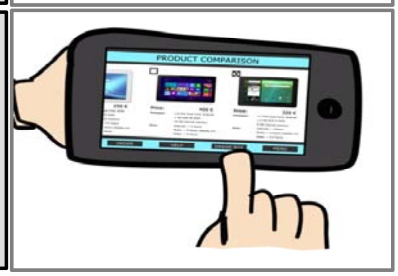


Figure 30: Mobile application scenario based on the customers own smart phones

Survey Design

Online survey method is chosen in this dissertation as it is more practical in terms of time and cost (Dillman, 2007; Thompson et al., 2003; Wright, 2005). LimSurvey, a free online survey application is used to implement the online survey. The principles identified by Dillman et al. (1998) and Dillman (2007) are followed while designing the survey. To ensure the consistency of the answers, returning to the previous question and jumping to the next question without answering are disabled. In addition saving and later resuming is enabled. However to submit the questionnaire all questions should have been answered. Following the recommendation of Valerie and Ritter (2007), 12-point Arial font has been used for the survey.

Considering the superiority of the seven-point Likert-scale in terms of reliability and validity of results (Cox III, 1980; Krosnick and Wright, 2010) especially for unsupervised surveys (Crano and Brewer, 2002; Finstad, 2010) and consistent with prior research on the IT acceptance, all items were measured using a seven-point Likert-scale.

The survey was started by introducing the web questionnaire with an inviting and instructive welcome screen. In addition, an incentive of entering into a drawing to win one of five, €25 gift certificates from Amazon was added into the greeting text to encourage participation in the survey. The questions about gender and age were presented in the beginning for two reasons: their answers are used for branching later on in the survey, they play an important role in lowering the chance for participants to abandon the survey and that by building investment (Valerie and Ritter, 2007). The final product was then the first draft of a self-administered cross-sectional questionnaire which included greetings, demographics-related questions and questions spanning the measurement items covering three scenarios. For each scenario, the same set of the questions were asked, with minor adaptation to the specific context.

The first draft of the questionnaire was presented and discussed with nine peers during a workshop. The revised version of the questionnaire has then been lunched for a pre-test. Throughout a two weeks' period, the pre-test online survey was conducted for two purposes: first, identifying any concerns linked to the survey's functionality, accessibility and length; second, to further improve and refine the questionnaire in provision for the main survey. 41 participants - mainly research associates - were completed the pre-test. According to the received feedback, participants found the survey to require a longer period of time to be completed than mentioned. The survey was fully functional, yet it included a number of minor design flaws. Also some of the items seemed to be unclear and required further explanation or rephrasing. Naturally, the necessary corrections and amendments were made. The questionnaire was also redesigned to allow a more logical progression.

Data Collection and preparation

To collect the data, the survey was accessible for two weeks starting on April 23rd, 2014. The participation was completely anonymous. Following the common practice in technology acceptance research, a non-probability sampling technique has been used. 4189 people – mainly students and staff of Hamburg University of Technology (Germany) - were invited via email to complete the survey. 635 emails were returned as undeliverable leaving a total of 3554 emails successfully sent. 548 participants started to answer the survey of which 308 did it to completion. After an initial screening of the data, 6 cases were removed from the sample by reason of suspicious patterns suggesting questionable responses. The resulting sample consisted of 302 cases, which is the equivalent to a final response rate of 8.5%. Considering that in technology acceptance studies the average number of participants is around 290 (ranging from 25 to 2,500) (Legris et al., 2003), with 302 participants, this dissertation holds above average sample size in the field.

Regarding demographics, while the mean age of the respondents was 31, 45.4% of respondents were under 25 years old, 34.4% were between 26 and 40 and 20.2% were older than 40 years old, with the age ranging from 18 to 83. Obviously, that indicates a predilection for younger people, which was expected considering the large number of students comprised in the sample and the nature of the survey channel. Regarding gender, the distribution is not far from balanced with 44.4% of the respondents being female and 55.6% being male. The majority of the participants have more than 15 years of experience with the Internet. They access the Internet several times a day (89.4%), are highly Internet-affine (59%) and consider the Internet to be their primary source of information (95.7%). Table 21 offers an overview of participant demographics.

However, the gender distribution is very close to the distribution of the gender in German population, for age and education, the representativeness of the data cannot be claimed. Nevertheless the representativeness of the data is of secondary importance for this dissertation, as the focus of the research is not on the estimation of the population parameters but on examination of the causal hypotheses (Göritz and Schumacher, 2000). Furthermore considering the exploratory nature of the current research nonrepresentative sample is appropriate (Bhutta, 2012; Göritz and Schumacher, 2000). The reason that non-probability sampling technique is frequently used in technology acceptance studies, particularly when the technology and the model are new (Aldás-Manzano et al., 2009; Davis et al., 1989; Ha and Stoel, 2009; Klopping and McKinney, 2004; Porter and Donthu, 2006; Wu and Wang, 2005).

Table 21: Participant demographics

Variable	Category	Frequency	In %	Mode
Gender	Male	168	55.6	Male
	Female	134	44.4	

Variable	Category	Frequency	In %	Mode
Age	Under 20	50	16.6	21-25
	21-25	87	28.8	
	26-30	59	19.5	
	31-40	45	14.9	
	41-50	15	5.0	
	51-60	27	8.9	
	61 or above	19	6.3	
Education	8th grade or less	3	1	Graduated from college, graduate or postgraduate school
	Some high school (Grade 9-11)	19	6.3	
	Graduated from high school	32	10.6	
	1-3 years of college/university	100	33.1	
	Graduated from college, graduate or postgraduate school	138	45.7	
	Refused to answer	10	3.3	
Job Status	Full-time job	112	37.1	Full-time student
	Part-time job/by the hour/occasionally	74	24.5	
	Unemployed	10	3.3	
	Retired	9	3.0	
	House wife /House husband	4	1.3	
	In professional education/traineeship/military service/civil service	12	4.0	
	Full-time student	122	40.4	
	Part-time student	14	4.6	
	Refused to answer	8	2.6	

5.2.3 Model Estimation and Results Assessment

Once the data set is ready, using the PLS-SEM method, the relationships in the path diagram can be estimated. SmartPLS software (SmartPLS 3.0 Professional) is chosen for the analyses of the research model. However, before using the SmartPLS software, algorithmic options and parameter settings must be selected (Hair et al., 2017).

In this dissertation, the recommendations of Hair (2012b) for initializing the PLS-SEM algorithm is followed. First, it must be decided by which weighting scheme the relationships between the latent variables will be estimated. Path weighting is particularly suitable in this context, as hereby explained variances of endogenous latent constructs are maximized (Chin and Newsted, 1999b; Hair et al., 2014a). Following the recommendations of Hair (2012b) and Hair et al. (2014a), using the SmartPLS, the row data is standardized with a mean of 0 and variance of 1. In addition, the maximum number of iterations is set at 300 and for the first iteration of the algorithm the values of 1 are specified for all relationships in the measurement model. Finally, the stop criterion of the algorithm is set at 10^{-5}. Once the algorithm is initialized, the data set is used to execute the PLS-SEM algorithm and generate the estimation results.

Having the estimation results, the next step is the assessment of the quality of the results or quality of the model, the goal here is to gauge how well the theoretical measurement and structural models fit the data (Hair et al., 2014a). To do so, there is a need for appropriate criteria, which in the context of PLS-SEM can ultimately assess the predictive ability of the model (Hair et al., 2014a). In PLS-SEM the quality of measurement and structural model is evaluated separately in a two-step process (Hair et al., 2011; Tenenhaus et al., 2005). Rationally, as the first step, before assessing the structural relationships, one should examine if the indicators can truly represent the corresponding constructs (Hair et al., 2011). To do so the validity and reliability of the indicators should be evaluated. Once the validity and the reliability of the measures proved, in the second step the quality of the structural model should be assessed (Hair et al., 2011). There are several works offering a comprehensive guide for the evaluation criteria and procedures of PLS-SEM result assessments (Chin, 1998b; Hair et al., 2014a, 2013, 2011; Henseler et al., 2009). Aligned with the proposed quality criteria of these works and in line with the two-step PLS-SEM assessment process, following the quality of measurement and structural models of this dissertation will be examined.

5.2.3.1 Quality Criteria for Measurement Model Assessment

Before starting the assessment process, it is imperative to know the nature of the relationships in measurement model, be it indicators reflecting the latent variable or forming it, considering that the modus operandi is not the same assessing the quality of results. Generally, there are two conceptually different approaches to generate measurement models (Sarstedt et al., 2016). The first approach is called reflective (Fornell and Bookstein, 1982). It assumes that the latent construct causes the measurement which is why, as shown in the first row of Figure 31, in its arrow scheme the arrows are pointing from the construct towards the measurement items. The logic of creating these indicators is that they all measure the same underlying concept which means in case of a change in the actual level of the latent variable, all indicators should also change in the same direction (Chin, 1998b; Fornell and Bookstein, 1982; Jarvis et al., 2003; Sarstedt et al., 2016). In the other words reflective indicators, also referred to as effect indicators are regarded as a "*representative sample of all the possible items within the conceptual domain of the construct*" (Hair et al., 2014a, p. 43). Thus they should be interchangeable, highly correlated and the omission of any of them should not have any repercussions on the meaning of the construct (Chin, 1998b; Fornell and Bookstein, 1982; Hair et al., 2014a; Jarvis et al., 2003; Sarstedt et al., 2016).

In contrast, the second approach referred to as the formative approach (Fornell and Bookstein, 1982) assumes the opposite that is the measurement items form the construct; mirroring this logic also in its arrow scheme with arrows pointing towards the construct as shown in Figure 31. Contrary to the case with the reflective model, deleting an item from the model potentially changes the nature of the construct (Hair et al., 2014a; Sarstedt et al., 2016). In a formative model, there are no expectations of correlation between the indicator variables; it even may cause problems due to the collinearity (Hair et al., 2014a; Jarvis et al., 2003). There are two types of formative models, models with causal indicators and models with composite indicators (Sarstedt et al., 2016). Whereas in the former, the indicators cover the totality of the causes of an underlying construct, in the latter they are rather contributors to a construct (Bollen, 2011; Sarstedt et al., 2016). Since often identifying each and every aspect around a phenomenon is not realistic, in formative models with causal indicators a construct-level error term representing the unidentified causes has been taken into account. In contrast, as their name implies, composite indicators form a composite fully representing a construct without any measurement error (Bollen, 2011; Sarstedt et al., 2016). PLS-SEM treats formative model indicators as composite indicators without construct level measurement error (Sarstedt et al., 2017).

Noting that, based on the definition of the constructs, in this dissertation only reflective measurement approach has been used for measurement model conceptualization and operationalization, the remainder of this section is dedicated to review of quality criteria solely for reflective model assessment.

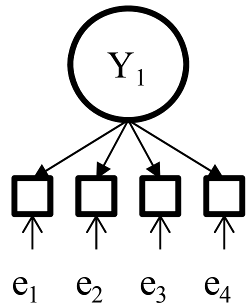
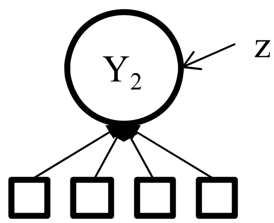
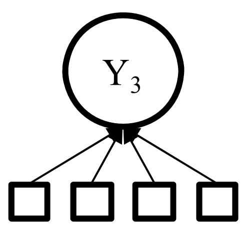
Reflective	**Effect Indicators**		➢The indicators are viewed as a representative sample of all the possible effects within the conceptual domain of construct ➢Relationships go from the construct to its indicators ➢Takes measurement error into account at the item level ➢Indicators should be correlated with each other ➢Dropping an indicator from the measurement model does not alter the meaning of the construct
Formative	**Causal Indicators**		➢The indicators are expected to cover all aspects of the content domain ➢Direction of causality is from measure to construct ➢Takes measurement error into account at construct level ➢No reason to expect that measures are correlated ➢Dropping and indicator from the measurement model may alter the meaning of the construct
Formative	**Composite Indicators**		➢Similar to causal indicators expect for following aspects: ➢The indicators are rather contributors to the underlying construct ➢No measurement error at construct-level

Figure 31: Reflective and formative measurement model conceptualization and operationalization adapted from Sarstedt et al. (2016, p. 4001)

5.2.3.1 Measurement Model Assessment

The quality of a reflective measurement model is assessed over two central criteria namely reliability and validity. As mentioned in the section 5.1.1, measurement of latent constructs with multiple variables reflects some error in addition to the true value of variable. In fact *"when indirect measures are used to gather data, measurement error is virtually guaranteed"* (Lowry and Gaskin, 2014, p. 127). The total measurement error is divided to systematic and random error; while random error threatens reliability, systematic error threatens the validity of a measurement (Hair et al., 2014a). A fully reliable measurement has a random measurement error of zero whereas a totally valid measurement has both random and systematic measurement error of zero (Churchill, 1987; Götz et al., 2010). To ensure the reliability of a reflective measurement model two criteria should be assessed namely indicator reliability and internal consistency reliability (composite reliability). The measurement criteria to assess validity are convergent validity and discriminant validity. In addition to above mentioned criteria, the significance of the indicator loadings should be examined in the measurement models. In the context of the PLS-SEM, this can be done using the non-parametric bootstrapping method (Hair et al., 2014a). For more extensive review of bootstrapping method see section 0.

Reliability is the degree to which a measurement model accurately measures a specific construct, regardless of whether it really comprehends the underlying concept of the construct. A reliable measurement does not produce random results and through repeated measurement, results remain stable and consistent (Iacobucci and Churchill, 2009; Straub, 1989) in other words, *"reliability is an index of consistency"* (Iacobucci and Churchill, 2009, p. 258). Therefore, usually the first step to assess the quality of reflective measurement model is assessing its individual indicator reliability and internal consistency reliability.

Individual indicator reliability

For each individual indicator, indicator reliability determines what proportion of its variance is explained by the corresponding construct (Henseler et al., 2009) and referred to as the variance extracted from the item, the remainder is the measurement error. Indicator reliability can have values between zero and one, the higher the value, the higher the reliability. The indicator reliability is denoted by $\rho_i = \lambda_i^2/[\lambda_i^2 + var(\varepsilon_i)]$ (Bagozzi and Yi, 2011, p. 17) where λ_i is the standardized outer loading of indicator i and $var(\varepsilon_i)$ is the variance of the measurement error of indicator i defined as $1 - {\lambda_i}^2$. (Chin, 1998b). In literature, the lower bound for standardized outer loading of an indicator is often considered as 0.708≈0.7, and accordingly the reliability as 0.50 which implies that at least 50% variance of an indicator should be explained by its corresponding latent variable (Bagozzi and Yi, 2011; Hair et al., 2011; Henseler et al., 2009;

Ringle and Spreen, 2007). However, these values shouldn't be applied rigidly, depending on the model and the sample size (Bagozzi and Yi, 2011; Fritz, 1995), the values lower than 0.5 could be still satisfactory if the corresponding construct do satisfactory in the overall model (Bagozzi and Yi, 2011). Therefore, it is recommended to consider indicators with loadings between 0.40 and 0.70 for removal only if that results in an increase in the internal consistency reliability (composite reliability) and/or the convergent validity (Bagozzi and Yi, 2011; Hair et al., 2014a). However "*results based on the retention of low-reliability items must be interpreted with caution*", bearing in mind that low reliabilities can negatively affect the estimated relationships between constructs (Hulland, 1999, p. 199). Items with very low loadings (< 0.40) should however be eliminated (Hair et al., 2014a, 2011; Henseler et al., 2009).

The estimated results for the aggregated data showed that the majority of the items´ loadings were satisfactory; except for three items: an item from personal innovativeness in IT (PIIT4) and two items for personal relevance (PR3 and PR4) (see the items in Table 18 and Table 20). PIIT4 had loadings lower than 0.4 and therefore was excluded. The PR3, and PR4 had loadings between 0.4 and 0.7, therefore their deletion impact on AVE and composite reliability was tested before deciding to retain or delete them. Following the recommendation of the Hair et al. (2014a) and after careful consideration, PR3 has been kept as the item's loading (0.66) was just slightly under the 0.7 threshold and its removal didn't engendered any proper increase in the AVE and/or the composite reliability. However, PR4 was deleted as its removal resulted in a healthy increase in AVE. Additionally, the second item of the importance construct, IMP2, was discarded for it presented very weak results in Scenario 3; satisfyingly, the removal of IMP2 resulted in a healthy increase of the AVE.

Internal consistency reliability

Internal consistency is a measure to determine how accurate a given latent construct is measured by its assigned indicators. In assessing the reliability of the measurement model, the reliability in the construct level is of more importance than indicator level (Bagozzi and Baumgartner, 1994). In the context of PLS-SEM, internal consistency is measured either by Cronbach's alpha (Cronbach, 1951) or by the composite reliability criterion (Werts et al., 1974). Hair et al. (2014a) recommend using composite reliability over Cronbach's alpha for it allows a better approximation of the reliability.

The value of composite reliability could vary between zero and one, where higher values indicate a higher reliability. The composite reliability is denoted by $\rho_c = (\sum_i \lambda_i)^2/[(\sum_i \lambda_i)^2 + \sum_i var(\varepsilon_i)]$ (Chin, 1998b, p. 320) where λ_i is the standardized loading between the construct and indicator i (Ringle, 2004c), and $var(\varepsilon_i)$ is variance of the measurement error defined as $1 - \lambda_i{}^2$. (Chin, 1998b). In exploratory research, values of 0.60 to 0.70 are usually viewed as satisfactory for composite reliability, in more advanced research stages, the threshold is slightly higher with values between 0.70 and 0.90 regarded as satisfactory (Hair et al., 2011, 2014a; Henseler et al., 2009). Accordingly values inferior to 0.60 are usually synonymous with the lack of reliability (Hair et al., 2014a) whereas values superior to 0.95 are typically not desirable for they usually indicate that "*all indicator variables are measuring the same phenomenon*" (Hair et al., 2014a, p. 102). That said, it is possible in some cases to have a composite reliability superior to 0.95 even though the indicators are in fact not similar nor do they cover exactly the same aspect (Chin and Dibbern, 2010).

An alternative criterion to measure internal consistency reliability is recently proposed by Dijkstra and Henseler (2015) referred to as reliability coefficient denoted by ρ_A which usually returns a value between Cronbach's alpha and composite reliability (Sarstedt et al., 2017).

Following the recommendation of Hair et al. (2014a), in the present study, composite reliability is used to measure the internal consistency reliability. All composite reliability values are clearly higher than 0.7 implying satisfactory accuracy of the measurement of each construct by its items. Nonetheless, composite reliability was observed to be higher than 0.95 in two constructs, namely BI and PE. The items for the constructs in question were adopted from the original works of Venkatesh et al. (2003, 2012) where they have demonstrated a good composite reliability. Thus, it is assumed that these high composite reliability values are simply exceptionally good and therefore no changes were deemed necessary. In addition the reliability coefficient is assessed. The results from reliability coefficient are as well higher than 0.7 expect for PR and IMP being slightly under 0.60. As in exploratory research, values of 0.60 to 0.70 for reliability are acceptable, it is suggested that all construct measures exhibit sufficient levels of internal consistency reliability.

After assessing the reliability of the measurement models, the next step is to evaluate the models' validity. Validity is the extent to which a measurement model measures what it is supposed to measure, that is the underlying concept of the latent variable (Iacobucci and Churchill, 2009). In the context of PLS-SEM, the validity of reflective measurement model is inferred by looking for two types of validity, namely convergent validity and discriminant validity.

Convergent validity

Convergent validity is the extent to which different measures of the same construct positively correlate and converge. For the assessment of the convergent validity, the above mentioned composite reliability criterion as well as a criterion called average variance extracted (AVE) are used. Both tests describe, how well a construct is explained by the totality of its indicators (Hair et al., 2009). AVE is denoted by $AVE_c = \sum_i \lambda_i^2 / [\sum_i \lambda_i^2 + \sum_i var(\varepsilon_i)]$ (Chin, 1998b, p. 321), the same as in reliability tests formulas, λ_i is the standardized loading between the construct and indicator i and $var(\varepsilon_i)$ is variance of the measurement error defined as $1 - {\lambda_i}^2$. Based on the same logic as indicator reliability, the values above 0.5 is considered as satisfactory; so that the total variance of indicators and their corresponding construct is greater than effect of measurement error (Hair et al., 2011; Ping Jr, 2004; Ringle, 2004c).

The second step in the measurement model assessment is the assessment of the validity of the measurement models; this is performed through the evaluation of model's convergent validity and discriminant validity. As discussed in the convergent validity section, the measurement criterion for the convergent validity is the AVE. AVE depicts the variance captured by the indictors relative to the measurement error (Fornell and Larcker, 1981). Customarily, an AVE that is higher than 0.50 is required to justify the use of the construct (Hair et al., 2014a).

In the case of the present research, all AVE values are superior to the 0.5 threshold value with 0.53 being the lowest estimate recorded for personal relevance (PR) meaning that all constructs of the model can, on average, explain more than the half of the variance of their indicators (Hair et al., 2014a).

Discriminant validity

Discriminant validity is defined as the degree of autonomy of different constructs in a given model. It is a case when the relationship between indicators measuring a construct is stronger than the relationship between indicators measuring different constructs (Fornell and Cha, 1994; Götz et al., 2010; Henseler et al., 2009). Three different approaches do exist in the literature for assessment of discriminant validity, namely cross-loading, Fornell-Larcker and HTMT. Well-known as a more liberal measure, cross-loading criterion is based on comparison of a given indicator's loadings through its associated construct with its loadings through other constructs in a given model (Hair et al., 2011, 2014a). In contrast Fornell-Larcker criterion often is referred to as a stricter method than cross-loadings. It suggests that average variance extracted of a latent variable should be greater than each squared correlation of the given latent variable with another latent variable in a given model (Fornell and Larcker, 1981), so that a construct shares more variance with its indicators than with the ones of any other construct (Hair et al., 2011, 2014a). Recently Henseler et al. (2015) introduced a new and more sensitive set of criteria for discriminant validity, referred to as HTMT (Heterotrait-monotrait). Based on a simulation study, they could show that the HTMT approaches outperform both previous methods in detecting lack of discriminant validity (Henseler et al., 2015). There are two different approaches to use HTMT to assess discriminant validity: first as a criterion with a pre-defined threshold and second as the input for a statistical discriminant validity test, commonly referred to as $\text{HTMT}_{\text{inference}}$ (Henseler et al., 2015). In the literature threshold for the criterion-based HTMT is 0.90 that is if the HTMT value, which is an estimate of the correlation between the indicators of two distinct constructs, is smaller than 0.90 then it can be concluded that these constructs are empirically distinct. However for the $\text{HTMT}_{\text{inference}}$, HTMT values are used to construct confidence intervals and test the null hypothesis, lack of discriminant validity ($H0$: $\text{HTMT} \geq 1$) against the alternative hypothesis, two constructs are distinct ($H1$: $\text{HTMT} < 1$).

To assess the discriminant validity in this study first the Fornell-Larcker criterion has been used. The results from Fornell-Larcker criterion analysis revealed no inadequacies except for three items: an item from behavior intention (BI3) and two items from performance expectancy (PE3 and PE4), that had been linked to discriminant validity problems. After carefully considering the measurements' content validity, these three items were removed from the original model. Then as recommended by Henseler et al. (2015), the more conservative method of the HTMT is used. The revised model's HTMT values, shown in Table 22, demonstrate satisfactory discriminant validity which implies that the model’s constructs are indeed positively distinct. All the results are below the conservative threshold of 0.85 except for two constructs of PE and BI which hold a HTMT value of 0.95. From theoretical point of view, these both constructs are conceptually different and are frequently used in previous technology acceptance studies. Therefore as also advocated by Henseler et al. (2015), in technology acceptance studies the choice of more liberal HTMT criterion is justified. In addition the bootstrapping procedure with 5000 samples, no sign changes option, and BCa bootstrap confidence intervals, and two-tailed testing at the 0.05 significance level (95% confidence interval) is conducted. The results of the more liberal HTMT approach ($HTMT_{inference}$), shown in Table 22, demonstrate that none of the HTMT confidence intervals contains the value 1, suggesting that all the HTMT values are significantly different from 1. Thus discernment validity has been met for all constructs of the model.

Table 22: Discriminant validity assessment – HTMT values and 95% confidence interval

	IP	BI	EE	PE	SI	HM	SOCP	SOLP	AO	IO	PR	IMP	PIIT
IP													
BI	0.785 [0.726;0.833]												
EE	0.365 [0.263;0.460]	0.499 [0.387;0.601]											
PE	0.793 [0.740;0.837]	0.954 [0.926;0.976]	0.480 [0.362;0.584]										
SI	0.697 [0.607;0.777]	0.796 [0.714;0.865]	0.433 [0.302;0.552]	0.820 [0.731;0.891]									
HM	0.718 [0.649;0.778]	0.757 [0.696;0.808]	0.276 [0.172;0.386]	0.770 [0.705;0.823]	0.751 [0.625;0.832]								
SOCP	0.382 [0.261;0.495]	0.363 [0.227;0.485]	0.163 [0.054;0.290]	0.363 [0.225;0.484]	0.361 [0.216;0.503]	0.492 [0.373;0.606]							
SOLP	0.324 [0.202;0.439]	0.355 [0.225;0.469]	0.254 [0.125;0.377]	0.352 [0.221;0.470]	0.361 [0.213;0.498]	0.324 [0.190;0.448]	0.543 [0.419;0.635]						
AO	0.352 [0.227;0.475]	0.458 [0.321,0.589]	0.409 [0.266;0.541]	0.424 [0.285;0.558]	0.331 [0.192;0.482]	0.334 [0.218;0.464]	0.318 [0.180;0.471]	0.331 [0.198;0.462]					
IO	0.348 [0.229;0.465]	0.371 [0.239;0.495]	0.254 [0.174;0.373]	0.426 [0.296;0548]	0.387 [0.230;0.522]	0.449 [0.328;0.570]	0.618 [0.488;0.739]	0.310 [0.171;0.453]	0.374 [0.235;0.510]				
PR	0.433 [0.294;0.575]	0.585 [0.435;0.732]	0.353 [0.173;0.519]	0.584 [0.440;0.724]	0.592 [0.431;0.753]	0.471 [0.319;0.647]	0.272 [0.147;0.456]	0.277 [0.145;0.449]	0.499 [0.329;0.701]	0.321 [0.165;0.523]			
IMP	0.235 [0.081;0.406]	0.392 [0.235;0.563]	0.058 [0.037;0.231]	0.400 [0.241;0.561]	0.355 [0.188;0.520]	0.266 [0.123;0.448]	0.153 [0.079;0.346]	0.297 [0.181;0.478]	0.314 [0.158;0.507]	0.212 [0.102;0.396]	0.324 [0.199;0.572]		
PIIT	0.394 [0.272;0.513]	0.458 [0.329;0.577]	0.511 [0.393;0.615]	0.386 [0.247;0.516]	0.463 [0.309;0.604]	0.411 [0.284;0.528]	0.328 [0.178;0.463]	0.349 [0.208;0.481]	0.427 [0.295;0.553]	0.324 [0.186;0.455]	0.319 [0.181;0.513]	0.051 [0.049;0.235]	

After applying the revisions stated above to meet all model evaluation assessment criteria, the indicators were recorded and the PLS-SEM algorithm was recalculated for the final model. The results for the revised model's measurement model are summarized in Table 23. Relying on the results, the quality criteria for measurement model are consistently met and thus it can be concluded that the current measurement model is reliable and valid.

In addition, the significance of the indicators has been examined to verify if indicators in a measurement model are indeed significant. The bootstrapping procedure with 5000 samples, no sign changes option, and BCa bootstrap confidence intervals, and two-tailed testing at the 0.05 significance level (95% confidence interval) is conducted. The results show that none of the confidence intervals include the value 1, therefore all items can be considered significant. Here, it is important to note that for the analyses of this dissertation, the assessment of the measurement models has been conducted for both aggregated data (aggregation of the data from all three scenarios) and data generated for each scenario.

Table 23: Results of quality assessment criteria for the measurement model (aggregated data)

Latent Variable	Indicator	Convergent validity			Internal consistency reliability		Discriminant Validity	Significant (p <0.05)?	95% BCa Confidence Interval
		Loading	Indicator reliability	AVE	Composite reliability	Reliability coefficient			
Behavioral Intention to Use (BI)	BI1: I would like to shop in stores which have such technologies.	0.973	0.95					Yes	[0.965;0.979]
	BI2: I would use this technology frequently.	0.969	0.95	0.940	0.979	0.968	Yes	Yes	[0.957;0977]
	BI3: I intend to use the presented technology if available.	0.967	0.95					Yes	[0955;0975]
Effort Expectancy (EE)	EE1: Learning how to use the presented technology seems easy for me.	0.959	0.93					Yes	[0.939;0.971]
	EE2: I think my interaction with this technology would be clear and understandable.	0.961	0.93	0.911	0.976	0.968	Yes	Yes	[0.941;0.973]
	EE3: The presented technology appears to be easy to use.	0.956	0.93					Yes	[0.937;0.968]
	EE4: It would be easy for me to become skillful at using the presented technology.	0.942	0.89					Yes	[0.919;0.959]

Performance Expectancy (PE)	PE1: I think using the presented technology will help me find what I want faster and easier in the shop.	0.923	0.85	0.892	0.961	0.941	Yes	Yes	[0.897;0942]
	PE2: The presented technology will make shopping more convenient for me.	0.958	0.93					Yes	[0.944;0.968]
	PE3: The presented technology will fit with my shopping needs.	0.952	0.91					Yes	[0.938;0.962]
Social Influence (SI)	SI1: My friends and/or family would be impressed to hear that I use this technology.	0.756	0.58	0.732	0.891	0.851	Yes	Yes	[0.687;0.811]
	SI2: My friends and/or family would be interested to use this technology.	0.928	0.85					Yes	[0.909;0.942]
	SI3: I think most people in my community will use the presented technology for shopping.	0.873	0.76					Yes	[0.819;0.909]
Hedonic Motivation (HM)	HM1: The presented technology will make the shopping more fun for me.	0.961	0.93	0.794	0.938	0.951	Yes	Yes	[0.951;0.969]

	HM2: I will enjoy shopping more in shops with this technology.	0.915	0.85					Yes	[0.894;0.931]
	HM3: The presented technology will make the shopping very entertaining.	0.929	0.87					Yes	[0.909;0.947]
	HM4: The presented technology would feel like playing a game for me.	0.742	0.54					Yes	[0.647;0.812]
Social Play (SOCP)	SOCP1:Internet gives you something to do with your friends	0.836	0.71	0.683	0.866	0.770	Yes	Yes	[0.768;0.811]
	SOCP2: Internet helps you to have fun with family or friends	0.856	0.74					Yes	[0.793;0.896]
	SOCP3: Internet helps you to be a part of events you enjoy without having to be there	0.785	0.63					Yes	[0.697;0.846]
Solitary Play (SOLP)	SOLP1: Internet helps you to stop thinking about work and problems after a hard day or week	0.902	0.81	0.776	0.912	0.878	Yes	Yes	[0.861;0.931]
	SOLP2: Internet helps you to relax when you are by yourself.	0.923	0.85					Yes	[0.887;0.946]

	SOLP3: Internet helps you to have something to do when nobody else is around.	0.815	0.66					Yes	[0.720;0.873]
Action Orientation (AO)	AO1: Internet helps you to decide where to buy certain products/services.	0.749	0.57	0.587	0.850	0.776	Yes	Yes	[0.671;0.812]
	AO2: Internet helps you to decide what to buy.	0.712	0.51					Yes	[0.603;0.788]
	AO3: Internet helps you to decide between alternative products/services.	0.813	0.66					Yes	[0.737;0.865]
	AO4: Internet helps you to decide whether to buy a certain product/service or not.	0.785	0.61					Yes	[0.718;835]
Interaction Orientation (IO)	IO1: Internet helps you to discover better ways to communicate with others.	0.819	0.68	0.684	0.866	0.792	Yes	Yes	[0.728;0.896]
	IO2: Internet helps you to think about how to act with friends, relatives, or people you work with.	0.876	0.78					Yes	[0.807;0.913]
	IO3: Internet helps you to get ideas about how to approach others in important or difficult situations.	0.784	0.61					Yes	[0.651;0.857]

Personal Relevance (PR)	PR1: It is important to me to feel like a smart shopper and to make successful purchases.	0.807	0.66	0.525	0.767	0.558	Yes	Yes	[0.712;0.868]
	PR2: It is important to me that the products I buy are consistent with my style.	0.703	0.49					Yes	[0.521;0.806]
	PR3: It is important for me to inform myself about the alternatives (e.g., price, quality) before making the purchase.	0.656	0.44					Yes	[0.491;0.777]
Importance (IMP)	IMP1: I often have trouble choosing which item to buy when I am shopping.	0.742	0.55	0.655	0.790	0.512	Yes	Yes	[0.485;0.886]
	IMP2: I would like to have some assistance when I am shopping, especially when the product I need is expensive.	0.872	0.76					Yes	[0.702;0.968]
Personal Innovativeness in IT (PIIT)	PII1: I like to experience products that use new technologies.	0.904	0.81	0.706	0.877	0.897	Yes	Yes	[0.870;0.928]
	PII2: Among my peers, I am usually the first to explore new information technologies.	0.698	0.49					Yes	[0.580;0.780]

	PII3: I feel comfortable using new information technologies.	0.902	0.81					Yes	[0.872;0.923]

5.2.3.2 *Quality Criteria for Structural Model Assessment*

After confirming the reliability and validity of the measurement models, the next step is dedicated to assessment of the quality of structural model's results. The goal here is to determine how well empirical data backs the developed conceptual model and consequently to be able to empirically confirm or reject the theoretical model (Hair et al., 2014a). As shown in Figure 27, this has to be done in 5 steps: assessing the structural model for collinearity, assessing the significance of structural model relationships (coefficient significance testing), assessing the predictive accuracy and effect size of each individual exogenous variable and as a last step, assessing the structural model's predictive relevance.

Collinearity test

Following the systematic approach to the assessment of structural model suggested by Hair et al. (2014a), the first step is assessing the structural model for collinearity issues. Since the path coefficients in a PLS-SEM are established based on multiple regressions, inheriting from a regular multiple regression, the path coefficients are subject to the risk of biased estimates if the independent variables significantly correlate, in other words if "*significant levels of collinearity among the predictor constructs*" exist (Hair et al., 2014a, p. 168). To assess collinearity two measures of tolerance and variance inflation factor (VIF) should be applied (Hair et al., 2014a; Henseler et al., 2009; Ringle and Spreen, 2007); tolerance indicates the amount of variance of an exogenous variable not explained by the other exogenous variables of a certain endogenous variable. VIF as reciprocal of the tolerance indicates whether the variance of an exogenous or predictor variable of a given endogenous construct explained by other exogenous variables of the same endogenous variable exceeds a critical level. The common variance of an independent latent variable with the other independent variables should not exceed 80%, which corresponds to a tolerance value of 0.20 and a VIF value of 5 (Hair et al., 2014a). Therefore tolerance levels below 0.20 and VIF values above 5 indicate a collinearity problem and should be treated either by merging the constructs, or creating higher-order constructs (Hair et al., 2014a). A more conservative threshold for VIF values is 3.3 that is VIF values of 3.3 or higher indicate a potential collinearity (Diamantopoulos and Siguaw, 2006).

In this study, VIF values smaller than 3.3 are considered adequate. Having four endogenous variables that are explained by multiple constructs entailed the examination of four sets. The results shown in Table 24, demonstrate the complete absence of collinearity issues, proven by VIF values lower than 3.3 for the constructs in all four sets. Naturally the tolerance measure is automatically satisfied for it is the reciprocal of the VIF.

Table 24: Collinearity assessment

First Set		Second Set		Third Set		Forth Set	
Constructs	**VIF**	**Constructs**	**VIF**	**Constructs**	**VIF**	**Constructs**	**VIF**
AO	1.20	AO	1.20	SOCP	1.24	EE	1.30
IO	1.13	IO	1.12	SOLP	1.24	PE	3.11
PIIT	1.17	PR	1.14			SI	2.31
		IMP	1.05			HM	2.41

Coefficient significance testing

The next step in structural model assessment is assessing the significance of the structural model's relationships to answer the question of whether an exogenous construct contributes significantly to the explanation of an endogenous construct and consequently to confirm or reject the theoretically derived relationships. Once paths are estimated by PLS-SEM algorithm, it is relatively easy to determine whether a certain hypothesis is supported or not by observing the estimates; the values are between -1 and +1. The signs show the direction of the relationship, either positive or negative. The closer the estimated path coefficient to 1, the stronger the relationship.

As said, one of the strengths of PLS-SEM is that it does not require the data to be normally distributed; therefore assessing the significance of the path coefficients is conducted using the non-parametric bootstrapping method (Good, 2005; Ringle and Spreen, 2007; Tenenhaus et al., 2005). Bootstrapping is a computer-based resampling method developed by Efron (1979) (Kline, 2011). Treating the available empirical data as a pseudo population, bootstrapping method generates a large number of random samples of the available empirical data by replacement; the number of cases should be exactly the same as the empirically collected data (Kline, 2011). At the beginning of a bootstrapping process, researchers pre-specify a number of bootstrap samples.

Once run, the PLS-SEM algorithm creates as many estimates as the number of bootstraps. Hair et al. (2014a) recommend 5.000 bootstrap samples to achieve robust bootstrapping results. The generated sub-samples are used to estimate the distribution of the total sample. This enables the PLS-SEM to calculate the standard error of all bootstrap samples for each path coefficient; it is then used in t-tests to measure the significance of path coefficients, in other words to check whether a path coefficient is significantly different from zero (Chin, 1998b; Hair et al., 2014a; Ringle, 2004c). The empirical t value is denoted by $t = \gamma_{ij}/se^{*}_{\gamma_{ij}}$ (Henseler et al., 2009), here γ_{ij} is the original estimate of the coefficient between the construct i and j and $se^{*}_{\gamma_{ij}}$ is the bootstrap standard error of γ_{ij}. Besides path coefficients, the bootstrapping method for the significance test can be applied for all parameter estimates of PLS-SEM (Henseler et al., 2009) such as indicator weights (in formative measurement models) and loadings (in reflective measurement models) by replacing the values of coefficients with the ones of loading or weights in the above-mentioned equation. If the empirical t value is smaller than a theoretical t value, it is assumed that the estimated parameters are not significantly different from zero, whereas if the empirical value is greater than theoretical t value, the null hypothesis can be rejected (Ringle and Spreen, 2007). The size of the theoretical or critical t values is based on the number of observations as well as the considered significance level (Henseler et al., 2009); for more than 30 observations, the normal quantiles can be applied to establish critical t values (Hair et al., 2014a). Referring to the commonly used critical values for two-tailed tests, empirical t value above 1.96 is considered significant at 5% significance level, respectively 2.57 at 1% and 1.65 at 10% (Hair et al., 2014a). However "the choice of significance level depends on the field of study and the study's objectives" (Hair et al., 2014a, p. 171).

Following the recommendation of Hair et al. (2014a), in this study, the number of bootstraps was set to 5000. Once the procedure was completed the results was compared to the threshold values for two-tailed tests. The common significance thresholds for the t-values are 2.57 for 99% confidence level, 1.96 for 95% confidence level and 1.65 for 90% confidence level (Hair et al., 2014a). The results were very satisfactory with the majority of path coefficients being significant at 99% confidence level; the path coefficient between the social play (SOLP) and hedonic motivation (HM) is significant at 95% confidence level and the path coefficient between the social influence (SI) and behavioral intention (BI) is significant at 90% confidence level.

Considering the exploratory nature of the current research the significance level of 10% has been chosen (Hair et al., 2014a). The only insignificant path coefficient is for the relationship between interaction orientation (IO) and effort expectancy (EE). Table 25 offers an overview of these results. Thereby 13 from 14 hypotheses formulated in the acceptance model of ubiquitous computing-based information services are confirmed. Explicitly all of the hypotheses regarding the relationships between the belief system and behavioral intention to use ubiquitous computing-based information services as well as those regarding the relationships between the personal innovativeness and involvement (importance and personal relevance) and the cognitive factors in belief system are confirmed. In addition, five out of six hypotheses formulated for the effects of the Internet dependency dimensions on belief system are confirmed. Only one hypothesis on the influence of interaction orientation on effort expectancy can't be confirmed and therefore is rejected.

Concerning the size of the path coefficients, it is to observe that performance expectancy (PE) has the largest path coefficient in comparison to the other direct determinants of the behavioral intention (BI) and thus the greatest effect on it. On the contrary, the path coefficient of the social influence (SI) and behavioral intention (BI) is the weakest. Therefore, by comparing the size of the path coefficients it can be concluded that performance expectancy is the most important determinant of the behavioral intention (BI) and social influence (SI) holds the most unimportant role in determining the behavioral intention (BI). Hedonic motivation (HM) then takes the second place before the effort expectancy (EE).

Table 25: Significance testing results for the structural model's path coefficients

Relationship	Path Coefficient	t Value	P Value	Significance level	95% BCa Confidence Interval
EE→BI	0.09	2.98	0.004	***	[0.028,0.153]
PE→BI	0.71	16.93	0	***	[0.623,0.797]
SI→BI	0.07	1.7	0.090	*	[-0.016,0.142]
HM→BI	0.15	3.15	0.002	***	[0.060,0.248]
BI→IP	0.77	28.34	0	***	[0.714,0.823]
AO→EE	0.19	3.43	0.001	***	[0.084,0.302]

AO→PE	0.18	3.04	0.002	***	[0.063,0.283]
IO→EE	0.07	1.37	1.359	ns	[-0.035,0.177]
IO→PE	0.23	4.23	0	***	[0.119,0.328]
SOCP→HM	0.35	6.11	0	***	[0.236,0.461]
SOLP→HM	0.14	2.36	0.021	**	[0.014,0.461]
PIIT→EE	0.43	8.57	0	***	[0.327,0.523]
PR→PE	0.29	5.81	0	***	[0.186,0.385]
IMP→PE	0.16	3.42	0.001	***	[0.065,0.251]

Note: ns = non-significant. *p <.10. **p <.05. ***p <.0.1.

Coefficient of Determination

The central criterion for the evaluation of the individual relationships in the structural model, known from regression analysis, is the coefficient of determination also referred to as R-squared (R^2) calculated for each existing endogenous latent variable in the structural model. "*When the case values of the latent variables are given by the weight relations, each inner structural model can be estimated by OLS with predictor specification and the explanatory power of each model can be evaluated by OLS's standard R^2's*"(Fornell and Cha, 1994, p. 69). Thus the coefficient of determination stands for the explained variance of an endogenous variable by its associated exogenous variables (Hair et al., 2012b, 2014a) and is the criterion for structural model's predictive accuracy. Aligned with its prediction-oriented approach, the goal of PLS-SEM is to maximize the explained variance; and obtain a high R^2 for the endogenous variables (Hair et al., 2011). R^2 threshold values are in fact subject to change depending on the research discipline and model complexity, for instance a value of 0.75 is regarded as high in success driver studies while 0.20 is viewed as high in disciplines such as consumer behavior (Hair et al., 2011, 2014a).

After assessing the significance of the path coefficient, next the coefficient of the determination should be assessed to verify the predictive accuracy of the structural model. Also referred to as the R^2, coefficient determination shows which portion of an endogenous construct's variance can be explained by the associated exogenous variable(s). Therefore, all R^2 values calculated for each exogenous variable in the structural model should be examined.

The R^2 values are between 0 and 1; the higher the value, the higher the predictive accuracy. The acceptance and interpretation of the R^2 values depend on the research discipline; whereas in marketing research the R^2 value of 0.75 is considered high in consumer behavior research, researchers consider R^2 value of 0.2 substantial (Hair et al. 2011; Hair et al. 2014). In current research while the R^2 of behavioral intention (BI) and intention to prefer (IP) respectively reaches the values of 0.85 and 0.6, the other endogenous variables cannot reach values over 0.3. That is performance expectancy (PE): 0.31, effort expectancy (EE): 0.31, hedonic motivation (HM): 0.19. In user acceptance studies, the R^2 values of 0.4 and 0.5 for behavior intention and use are considered as substantial (Venkatesh et al., 2012). However for customers' perceptions as effort expectancy, performance expectancy and hedonic motivation, the R^2 values above 0.3 are rarely observed (Agarwal and Prasad, 1999; Lu et al., 2005; Venkatesh and Bala, 2008). Therefore, the obtained R^2 values for the current model are considered rather high.

Effect size

After assessing the total effect of exogenous variables on an endogenous variable, the next quality measure is to verify if the effect of each of assigned exogenous variable is substantial; this measure is referred as effect size (Chin, 1998b; Hair et al., 2014a; Ringle and Spreen, 2007). To do so, the R^2 of the endogenous variable should be calculated by one at a time elimination of exogenous variables, the difference between R^2 before the deletion of a particular independent variable and after that can be used for calculation of its effect size (Hair et al., 2014a). The effect size is denoted by $f^2 = (R^2included - R^2excluded)/(1 - R^2included)$ (Chin, 1998b) where $R^2included$ and $R^2excluded$ are the R^2s obtained when the predictor latent variable respectively is used or not. According to Chin (1998c), f^2 values of 0.02, 0.15 and 0.35 can be regarded as small, medium and large.

The results obtained from the PLS-SEM algorithm show that the effect sizes of performance expectancy (PE) on behavioral intention (BI) with the value of 1.07 and behavior intention (BI) on intention to prefer (IP) with the value of 1.48 are large. The other exogenous constructs tend to have medium or small effect sizes on their associated endogenous constructs. Only the effect size of the social influence (SI) on behavioral intention (BI), 0.013, is under the threshold of 0.20. It is important to note that as the relationship between interaction orientation (IO) and effort expectancy (EE) is already rejected, its effect size is not considered relevant for further analyses.

Predictive relevance

An additional assessment of structural model involves a criterion only applicable for the endogenous variables with reflective measurement model known as the predictive relevance. It is a measure of the capability of the structure and the measurement model to derive the predictions (Hair et al., 2011; Tenenhaus et al., 2005). That is how well the empirical data can be reconstructed by the model and its parameter estimates (Chin, 1998b; Fornell and Cha, 1994). Indicator of the predictive relevance is Stone-Geisser's Q^2 value (Geisser, 1974; Stone, 1974). In the context of PLS-SEM, Stone-Geisser test criterion pursues a blindfolding procedure which systematically omits part of the raw data matrix for the indicators of the endogenous constructs during the parameter estimations, next, the estimates are used to predict the omitted data treated as missing values (Chin, 1998b; Henseler et al., 2009; Ringle and Spreen, 2007). The procedure iterates until all data points have been once gone through the procedure (Hair et al., 2014a). The value of Q^2 then is calculated by comparison of the actual data with the predicted ones. Mathematically, $Q2$ is denoted by $Q^2 = 1 - (\sum_D E_D / \sum_D O_D)$ (Chin, 1998b), where E is the sum of squares of prediction error and O is the sum of squares of the original values, and D is the blindfolding procedure distance between two consecutive elimination and prediction cases (Chin, 1998b; Tenenhaus et al., 2005). Predictive relevance is demonstrated when Q^2 values are above zero; failing that, negative values would indicate that the model is not capable of predicting raw data better than a simple mean estimation so it can be assumed that the model lacks predictive relevance (Chin, 1998b; Fornell and Cha, 1994; Götz et al., 2010; Hair et al., 2014a). Through the process of elimination, it is possible to measure the contribution of each exogenous variable to the predictive relevance. Similar to the effect size f^2, q^2 values as relative measures of predictive relevance are calculated for each exogenous variable. The same as effect size q^2 values of 0.02, 0.15 and 0.35 can be regarded as small, medium and large (Hair et al., 2014a; Henseler et al., 2009).

Predictive relevance is the last aspect which should be examined in the assessment of the structural model. To assess the predictive relevance of the current structural model, the blindfolding procedure with d=7 was conducted. The resulting values were satisfactory with all five Q^2 values being different from zero. Table 26 shows the calculated R^2 and Q^2 values for the endogenous variables of the current structural model.

Table 26: Results of the R^2 and Q^2

Endogenous Variable	R^2 Value	Q^2 Values
Behavior Intention (BI)	0.85	0.80
Effort Expectancy(EE)	0.31	0.28
Performance Expectancy (PE)	0.31	0.28
Hedonic Motivation (HM)	0.19	0.15
Intention to Prefer(IP)	0.60	0.60

In addition, the q^2 values are estimated for each exogenous variable. The registered q^2 results are sufficient to prove the predictive relevance. Only in two instances the effects are not satisfactory that is the relationship between the social influence (SI) and behavioral intention (BI) and the relationship between solitary play (SOLP) and hedonic motivation (HM).

Assessing the quality of results for the structural model shown in Table 27, it can be concluded that, in general, the empirical data supports the conceptual model of this dissertation. All of the relationships in the structural model are confirmed with the exception of the hypothesis H8. Furthermore, the results of the R^2 and Q^2 prove that the model possesses a sufficient explanatory power.

Table 27: Summery of structural model's quality criteria results

Endogenous variable	Exogenous variable	Path coefficient	Hypothesis		VIF (<5)	T Value (≥1.65)	f^2 (≥0.02)	Q2 (>0)	q^2 (≥0.02)
Behavior Intention (R^2=0.85)	Effort Expectancy	0.09	H1	✔	1.30	2.98	0.04	0.8	0.03
	Performance Expectancy	0.71	H2	✔	3.11	16.93	1.07		0.74
	Social Influence	0.07	H3	✔	2.31	1.7	0.013		0.009
	Hedonic Motivation	0.15	H4	✔	2.41	3.15	0.06		0.04

Effort Expectancy (R^2=0.31)	Action Orientation	0.19	H6	✔	1.20	3.43	0.04		0.03
	Interaction Orientation	0.07	H8	✘	1.13	1.37	0.007	0.28	0.005
	Personal Innovativeness in IT	0.43	H12	✔	1.17	8.57	0.22		0.194
Performance Expectancy (R^2=0.31)	Action Orientation	0.18	H7	✔	1.20	3.04	0.04		0.03
	Interaction Orientation	0.23	H9	✔	1.12	4.23	0.07	0.28	0.06
	Personal Relevance	0.29	H13	✔	1.14	5.81	0.11		0.09
	Importance	0.16	H14	✔	1.05	3.42	0.04		0.03
Hedonic Motivation (R^2=0.19)	Social Play	0.35	H10	✔	1.24	6.11	0.12	0.15	0.1
	Solitary Play	0.14	H11	✔	1.24	2.36	0.02		0.009
Intention to Prefer (R^2=0.60)	Behavioral Intention	0.77	H5	✔		28.34	1.48	0.6	

5.2.4 Assessing the Influence of Categorical Moderator Variables

Analyzing a PLS-SEM model, often it is essential to check the systematic influence of some additional variables on the direct paths between dependent and independent variables. The rational for the inclusion of such variables is that the collected empirical data is often from respondents with heterogeneous perceptions of latent variables which may result in significant differences in a given paths between different respondent groups (Hair et al., 2012b, 2014a; Sarstedt et al., 2011b). The lack of consideration of heterogeneity in the data may result in erroneous interpretations of the results; therefore it can be a serious threat to the validity of the PLS-SEM results (Hair et al., 2014a; Sarstedt et al., 2011b).

In technology acceptance studies, the existing heterogeneity within a data set is associated with three distinct categories namely organizational factors, technology factors, and individual factors (Sun and Zhang, 2006). Among Individual factors, age and gender are considered as the most prominent factors with a strong impact on individual's perceptions (Nosek et al., 2002) particularly perceptions of technology (Morris et al., 2005; Venkatesh et al., 2003; Venkatesh and Morris, 2000). Through a comprehensive literature review in technology acceptance studies, Niehaves and Plattfaut (2014) state that age and gender are the most used socio-demographic variables, respectively used in 87% and 95% of the reviewed studies followed by income and education used in only 9% and 10% of the studies. More extensively discussed in section 4.3.5, in this study the individual factors of age and gender are considered as categorical moderator variables of the direct relationships of UTAUT2.

In addition, aligned with the objectives of this dissertation, two factors namely service and technology type are hypothesized to influence the strengths of UTAUT2 relationship. However, despite age and gender, the goal is not to examine heterogeneity in technology related beliefs within different age and gender groups but to assess the heterogeneity in individuals' perceptions concerning different technology and services.

In general, moderator variables can be divided into two categories namely metric or categorical (Henseler and Fassott, 2010). Depending on whether the moderator is a latent variable measured with metric data or a single item variable measured with nominal data, distinct methods have been used for the estimation of the moderator effects. In the case of moderator being a metric and continuous variable, the product term approach is used and in the case of moderator being a single categorical variable, a group comparison method is applied (Henseler and Fassott, 2010). Indeed "t*he grouping variable is nothing more than a categorical moderator*" (Henseler and Fassott, 2010, p. 715). It is important to note that if the metric data can be transformed to the categorical data, also a group comparison method can be applied (Rigdon et al., 1998) for example, transforming the metric variable of age to younger and older categories. As in this dissertation only the group comparison approach is used, the remainder of this section is only dedicated to a discussion about this method.

Applying a group comparison, the observations are divided into different groups based on the categorical moderator variable (Rigdon et al., 2010). Then the model is estimated for each group and the path coefficients are compared. If a path coefficient in one group differs significantly from the one in the other group, it can be assumed that a moderating effect exists.

In PLS-SEM literature, there are several approaches to test the significance of differences among two groups (Hair et al., 2017):

- Parametric test: suggested by Chin (2000) and later introduced by keil et al. (2000), in this approach, firstly the model parameters for each group is estimated and then the standard errors generated form bootstrapping are used as input for the parametric test (Henseler, 2007; Sarstedt et al., 2011b).
- Permutation: as a response to the methodic shortcoming of the parametric approach in the PLS-SEM, that is holding distribution assumptions in a distribution-free method (Henseler et al., 2009), Chin (2003) introduced and elaborated (Chin and Dibbern, 2010; Dibbern and Chin, 2005) a nonparametric method also called product indicator approach. In this approach, the actual observed group differences are compared with those between randomly generated groups.
- PLS-MGA: Henseler (2007) proposed another nonparametric approach for PLS-SEM multi-group analysis (PLS-MGA) which seeks the differences between groups by comparing bootstrapping results of one group with that of the other group (Henseler et al., 2009; Sarstedt et al., 2011b).

Heir et al. (2017) recommend to use permutation test to multi group analysis. They also state that applying multiple methods provide additional confidence in the final results. Therefore for the multi group analyses of this dissertation both permutation and PLS-MGA methods are chosen for the multi-group analyses except for the analysis of differences in the age groups for which only PLS-MGA method is used. As the size of the one group is more than the double the size of the other group (Hair et al., 2017).

Besides the above-mentioned methods to test the pre-identified moderators, the use of PLS-SEM FIMIX can help to reveal unobserved heterogeneity in the data set (Hair et al., 2014a; Sarstedt et al., 2011a). The FIMIX procedure is applied for the given data set but no meaningful results could be extracted.

To assess the influence of the categorical moderators, the relationships in the path diagram should be estimated for each group. Here the same practice used for the quality assessment of the overall model should be applied to gauge how well the theoretical measurement and structural models fit the new data sets. Therefore, first the PLS-SEM quality criteria to verify the reliability and validity of the measurement models for each new data set are assessed. The results of the quality criteria for measurement model assessment for all groups are satisfactory without reservation.

In addition, to ensure the validity of the group analysis results, prior to analysis, measurement invariance should be tested. Established measurement invariance ensures that the variations in model estimates are not originated in distinctive content and meanings of the latent variables but indeed in true differences of structural relationships (Hair et al., 2017; Henseler et al., 2016). Recently Henseler et al. (2016) developed a procedure enabling to test the measurement invariance in PLS-SEM models referred to as measurement invariance composite models (MICOM) procedure. This procedure involves three steps: the first step referred to as configural invariance, ensures the identical specification of latent variables across the groups. That is if indicators per measurement model, data treatment, and algorithm setting are identical across the groups. Once the configural invariance is established, the next steps focus on systematic error of measures (Henseler et al., 2016). In the second step, referred to as compositional invariance, it is assessed if the composites are formed identically across groups. When both configural invariance and compositional invariance exist, it can be concluded that a partial measurement invariance which is a necessary and sufficient condition for conducting a multi group analysis is established. In the final step, the equality of composite mean values and variances are assessed. Having equal composite means and variances, it can be concluded that full measurement invariance is established and multi group analysis as well as pooling of data would result in valid outcomes and interpretations.

To ensure the validity of the group analysis results in this dissertation the MICOM approach is applied to test the measurement invariance of the given composites. As the PLS path models as well as data treatment used in all groups are alike and identical algorithm settings are used to calculate the model estimates, it is concluded that the configural invariance is established. The analyses for step 2 and step 3 of MICOM procedure are addressed below distinctly for each multi group analysis.

5.2.4.1 Age

To analyze the effect of age, it is necessary to delineate the age group categories, which then can be compared. The question here is how to define a theoretically sound cut-off point to create age groups. Therefore, next, the theoretical basis of the age group selection for this dissertation is discussed and the cut-off point for age groups is defined.

There are consistent empirical evidences that age differences are not only caused by pure aging effects but also birth periods are important sources of behavior variation between different age groups (Gunter and Furnham, 1992; Hofer and Sliwinski, 2006; Rogler, 2002; Ryder, 1965; Zuschlag and Whitbourne, 1994). Individuals born in a certain period of time often experience some unique historical circumstances surrounding their birth period; such shared experiences contribute to shaping their long-term value system which virtually stays unchanged through life (Meredith and Schewe, 2002). Therefore, in the literature there are different overlapping and related concepts addressing the age effects and categorization.

Age group is defined as "*a segment of a population that is of approximately the same age or is within a specified range of ages*" (Marriam-Webster, 2016). Cohort is a group of individuals who based on their date of birth, all have gone through a certain period of time and more or less have experienced the same micro- and macro-historical events (Ryder, 1965). As the term cohort literally means division into ten years, in the literature cohort groups are often divided by ten-year periods (Markert, 2004; Ryder, 1965). Generation on the other hand, usually encompasses a broader range of ages in a single group as the central focus of this categorization is not the birth period but certain historical circumstances surrounding that period (Markert, 2004). While the term cohort mostly bears a chronological meaning, the concept of generation uses a common determining experience for the delimitation and definition of a generation. Alike cohort, members of a generation are sharing some common historical orientation, however the corresponding birth period can span over twenty years (Markert, 2004). Hence, one generation may include two or more cohort groups.

There are various generational labels in marketing literature (e.g. baby boomers, generation X, generation Y, millennial generation, generation of digital natives, Net generation etc.). Labeling the whole members of a group with a single symbolic term expressing the collective characteristics of that group makes marketing efforts practical and manageable (Markert, 2004). Furthermore based on the findings of several empirical studies on intragenerational differences, Markert (2004) concludes that usually generational influences are greater than cohort influences.

Referring to the research objectives of this dissertation, more relevant for the analyses are generations, which are delimited and defined due to the determining technical events relating to the use of the digital technologies. By and large, in the history of mankind, individuals who experience the technologies developed for general population (e.g. Internet) in their early life are more advanced in the use of these technologies and are quite comfortable with these technologies in their later years (Scialfa and Fernie, 2006). As the famous quote of the computer pioneer, Alan Kay, says: "*technology is anything that was invented after you were born*" (e.g. see the quote in Geer, 2006; S.-J. Hong et al., 2013).

Taking a generational view, Prensky (2001) divides the present population into two groups; digital natives as those who grew up with digital media (e.g. Internet), and those who came of age before the introduction of the digital media whom he labels as digital immigrants. This generational terminology highlights the differences between two age groups suggesting that digital immigrants usually no more can learn to deal with digital media so naturally and quickly as digital natives (Palfrey and Gasser, 2010; Prensky, 2001, 2005). Digital natives are native speakers of the digital language of computers and the Internet, however digital immigrants have come to use digital technologies later in their lives and similar to learning a new language they have a form of accent (Prensky, 2001). Prensky (2005) describes various cognitive differences of digital natives and digital immigrants associated with growing up with different digital media e.g., better visual skills, more spatial skills, and abstract reasoning through use of computer-based applications. Based on these differences, digital natives and digital immigrants may perceive the benefits of digital technologies differently resulting in differences in their behavioral approaches in regard to digital technologies (Palfrey and Gasser, 2010; Prensky, 2001).

However, Prensky doesn't define the exact birth period for his generational categorization, in information system research literature, people who born after 1980 are often considered as digital natives and the ones who born before 1980 as digital immigrants (Kirk et al., 2012; Palfrey and Gasser, 2010; Resatsch et al., 2008; Thompson, 2013). The rationale is based on the advent of the Internet in the early 1990s, as the people born after 1980, were at most yet in their formative years using the Internet.

Based on the above-mentioned arguments, in this dissertation the generational approach of Prensky is used to identify the cutoff point for age groups. As discussed, members of digital native and digital immigrant generations are different in their perceptions of digital technologies and consequently their behavior regarding these technologies. It might be argued that considering interindividual differences, there could be heterogeneity within the members of native or immigrant groups. Therefore, it is important to note that, by taking the generational view this dissertation does not claim a complete homogeneity for all members of a generation. However, it assumes that for the use of digital technologies as in-store ubiquitous computing-based information services, the influence of intergenerational native or immigrant status is greater than the intragenerational differences. Therefore, to explore the moderation effect of age by multi-group analysis, the continuous variable of age is dichotomized; the complete sample including 302 cases is divided into two age groups. Following the common practice in information system research, the birth year of 1980 is chosen as a cutoff point. The first age group is composed of the participants with the age equal or younger than 34 (227 cases) at the day of the survey and the rest of participants with the age greater than 34 (75 cases) are the members of the second group.

After defining the age groups, the relationships in the path diagram can be estimated for each age group and the significance of the differences can be assessed. However, prior to multi group analysis, permutation test in Smart-PLS is run to create required values for the step 2 and 3 assessments of MICOM procedure. Table 28 summarizes the MICOM results. For all of the composites the full measurement invariance is established, except for BI which holds partial measurement invariance.

Table 28: Summary of MICOM results for age groups

MICOM Step 1				
Configural variance established? Yes				
MICOM Step 2				
Composite	**Correlation c**	**5% quantile of the empirical distribution of c_u**	**P Value**	**Compositional invariance established?**
BI	1.000	1.000	0.325	Yes
EE	1.000	1.000	0.327	Yes

PE	1.000	1.000	0.856	Yes
SI	1.000	0.996	0.692	Yes
HM	0.999	0.997	0.457	Yes
MICOM Step 3				
Composite	**Difference of the composite's mean value (= 0)**	**95% confidence interval**	**P value**	**Equal mean values?**
BI	0.326	[-0.275;0.269]	0.011	No
EE	0.141	[-0.244;0.268]	0.302	Yes
PE	0.235	[-0.267;0.264]	0.085	Yes
SI	0.268	[-0.267;0.269]	0.050	Yes
HM	0.016	[-0.277;0.247]	0.924	Yes
Composite	**Logarithm of the composite's variances ratio (= 0)**	**95% confidence interval**	**P value**	**Equal variances?**
BI	-0175	[-0.371;0.425]	0.418	Yes
EE	0.083	[-0.535;0.687]	0.783	Yes
PE	-0.250	[-0.358;0.443]	0.226	Yes
SI	-0.270	[-0.345;0.411]	0.197	Yes
HM	-0.171	[-0.292;0.357]	0.280	Yes

As the size of the one group is more than the double the size of the other group, to investigate the significance of the differences between the path coefficients, only PLS-MGA method is applied. The results are listed in Table 29. As can be seen, all of the path coefficients for the relationships between behavioral intention (BI) and its direct antecedents do differ between two age groups. An examination of the significance of group differences is usually carried out when the given path is significant in both groups. As shown in Table 29, only the relationship between performance expectancy (PE) and behavioral intention (BI) is significant for both groups with a higher path coefficient for the older group than for the younger group. As the difference is significant in 1% level, it can be assumed that age has a significant effect on the PE-BI relationship, but this influence is opposed to the hypothesized direction. Therefore, the hypothesis H2.1 is rejected.

Regarding the other relationships in the model, either both or one of the path coefficients are insignificant. The relationship between the social influence (SI) and behavioral intention (BI) is insignificant in both groups; therefore, the hypothesis 3.1 cannot be confirmed. However, the relationships of effort expectancy (EE) and hedonic motivation (HM) with behavioral intention (BI) are significant only for younger group; having a significant path coefficient for one group and insignificant for the other group can still deliver important information concerning the moderator effects. Based on these results, it can be assumed that effort expectancy (EE) and hedonic motivation (HM) are the determinants of behavioral intention only for younger group. Therefore, age can be considered as a moderator factor for these relationships. Regarding the relationship between the effort expectancy (EE) and behavioral intention (BI), the empirical results are opposed to the hypothesized direction. Therefore, the hypothesis H1.1 is rejected. However, as hypothesized, age influences the effect of hedonic motivation on behavior intention to use such that the effect is stronger for younger people than older people. Therefore, the hypothesis H4.1 is confirmed.

Table 29: PLS-MGA results for age

Relationship	Age groups	Path coefficient	Standard error	t-Value (≥1.65)	Group1 vs. Group 2		
					|Path coefficients -diff|	p-Value	Significant level
EE→BI	Group 1: ≤34	0.121	0.041	2.945	Group 2 ns	n/a	n/a
	Group 2: >34	0.023	0.031	0.752			
PE→BI	Group 1: ≤34	0.647	0.050	12.871	0.251	0.008	***
	Group 2: >34	0.898	0.062	14.322			
SI→BI	Group 1: ≤34	0.061	0.044	1.389	Both groups ns	n/a	n/a

	Group 2: >34	0.051	0.066	0.778			
HM→BI	Group 1: ≤34	0.197	0.055	3.594	Group 2 ns	n/a	n/a
	Group 2: >34	0.012	0.065	0.190			

Note: n/a = not applicable. ns = non-significant. *p <.10. **p < .05. ***p <.01.

5.2.4.2 Gender

The categorization of gender is straightforward with two categories encompassing either female or male participants. A dummy variable is used to represent female and male. The first group is dedicated to the female participants with 134 cases and the second group to the male participants with 168 cases. Table 30 summarizes the results of the MICOM procedure. Based on these results it can be concluded that full measurement invariance is established for all of the latent variables and multi group analysis is feasible.

Table 30: Summary of MICOM results for gender groups

MICOM Step 1				
Configural variance established? Yes				
MICOM Step 2				
Composite	**Correlation c**	**5% quantile of the empirical distribution of c_u**	**P Value**	**Compositional invariance established?**
BI	1.000	1.000	0.252	Yes
EE	1.000	1.000	0.372	Yes
PE	1.000	1.000	0.417	Yes
SI	0.997	0.995	0.035	Yes
HM	0.997	0.996	0.027	Yes
MICOM Step 3				
Composite	**Difference of the composite's mean value (= 0)**	**95% confidence interval**	**P value**	**Equal mean values?**
BI	0.127	[0.222;0.212]	0.275	Yes
EE	-0.051	[-0.220;0.219]	0.654	Yes

PE	0.198	[-0.221;0.222]	0.075	Yes
SI	0.184	[-0.234;0.223]	0.114	Yes
HM	0.168	[-0.227;0.218]	0.139	Yes
Composite	**Logarithm of the composite's variances ratio (= 0)**	**95% confidence interval**	**P value**	**Equal variances?**
BI	-0.035	[-0.359;0.351]	0.840	Yes
EE	-0.078	[-0.512;0.495]	0.740	Yes
PE	-0.145	[-0.334;0.313]	0.398	Yes
SI	0.026	[-.0361;0.339]	0.886	Yes
HM	0.176	[-0.291;0.281]	0.229	Yes

Table 31 and Table 32 respectively summarize the estimation results for permutation test and PLS-MGA for gender groups. The results for both methods are almost identical. As can be seen, the path coefficients for the relationships of performance expectancy (PE) and hedonic motivation (HM) with behavioral intention (BI) are significant for both gender groups, however comparing the group differences, no significant difference can be observed. Therefore, the hypotheses H2.2 and H4.2 are rejected. Similar to age groups, the effect of social influence (SI) on behavioral intention (BI) is insignificant for both gender groups. Therefore, the hypothesis H3.2 cannot be confirmed. The relationship between effort expectancy (EE) and behavioral intention (BI) is only significant for the male group, therefore it can be assumed that the influence of effort expectancy (EE) on behavioral intention (BI) is moderated by gender such that the effect is only significant for men, but this effect is opposed to the hypothesized direction. Therefore, the hypothesis H1.2 is rejected.

Table 31: Permutation test results for gender

Relationship	Service groups	Path coefficient	Standard error	t-Value (≥1.65)	Group1 vs. Group 2			
					Path coefficients -diff	95% confidence interval	p-Value	Significant level
EE→BI	Group 1: female	0.022	0.047	0.469	Group 1 ns	n/a	n/a	n/a

	Group 2: male	0.134	0.042	3.178				
PE→BI	Group 1: female	0.703	0.069	10.161	-0.021	[-0.231;0.224]	0.830	ns
	Group 2: male	0.725	0.059	12.728				
SI→BI	Group 1: female	0.055	0.060	1.487	Both groups ns	n/a	n/a	n/a
	Group 2: male	0.073	0.049	0.366				
HM→BI	Group 1: female	0.202	0.077	2.637	0.098	[-0.233;0.243]	0.336	ns
	Group 2: male	0.103	0.053	1.962				

Note: n/a = not applicable. ns = non-significant. *p <.10. **p <.05. ***p <.01.

Table 32: PLS-MGA results for gender

Relationship	Gender groups	Path coefficient	Standard error	t-Value (≥1.65)	Group1 vs. Group 2		
					| Path coefficients -diff |	p-Value	Significant level
EE→BI	Group 1: female	0.022	0.047	0.469	Group 1 ns	n/a	n/a
	Group 2: male	0.134	0.042	3.178			
PE→BI	Group 1: female	0.703	0.069	10.161	0.021	0.809	ns
	Group 2: male	0.725	0.059	12.728			
SI→BI	Group 1: female	0.055	0.060	1.487	Both groups ns	n/a	n/a
	Group 2: male	0.073	0.049	0.366			
HM→BI	Group 1: female	0.202	0.077	2.637	0.098	0.275	ns
	Group 2: male	0.103	0.053	1.962			

Note: n/a = not applicable. ns = non-significant. *p <.10. **p <.05. ***p <.01.

5.2.4.3 Service Type

To this point, all reported results are based on the aggregated data from all scenarios. However, to examine the moderator effects of service and technology type the consistency of the results between different scenarios should be examined. To do so, first, the structural model should be calculated for all scenarios and the results should be compared to explore if there is any significant difference between the services in different stages of information search and between the acceptance of mobile and stationary technologies.

As thoroughly discussed in data collection section, two distinct scenarios (scenario 1 and scenario 2) for a store based technology are developed from which scenario 1 is dedicated to services in information screening and search stage and scenario 2 is dedicated to services in alternative evaluation stage. Therefore, to empirically examine the moderator effects of service type the dataset from scenario 1 encompassing the participants' answers concerning the information search services is defined as the group 1 (302 cases). Correspondingly, the dataset from scenario 2 is defined as group 2 (302 cases) representing participants' perception about the alternative evaluation services.

Based on the MICOM results summarized in Table 33, it can be concluded that full measurement invariance is established for all given multi-item constructs except. Thus multi group analysis can be conducted with confidence.

Table 33: Summary of MICOM results for service type

MICOM Step 1				
Configural variance established? Yes				
MICOM Step 2				
Composite	**Correlation c**	**5% quantile of the empirical distribution of c_u**	**P Value**	**Compositional invariance established?**
BI	1.000	1.000	0.126	Yes
EE	1.000	1.000	0.403	Yes
PE	1.000	1.000	0.077	Yes
SI	1.000	0.998	0.866	Yes
HM	1.000	0.998	0.577	Yes

MICOM Step 3				
Composite	**Difference of the composite's mean value (= 0)**	**95% confidence interval**	**P value**	**Equal mean values?**
BI	0.055	[-0.164;0.165]	0.510	Yes
EE	0.053	[-0.158;0.155]	0.518	Yes
PE	0.156	[-0.167;0.156]	0.042	Yes
SI	0.082	[-0.161;0.158]	0.341	Yes
HM	0.135	[-0.161;0.164]	0.095	Yes
Composite	**Logarithm of the composite's variances ratio (= 0)**	**95% confidence interval**	**P value**	**Equal variances?**
BI	-0.077	[-0.208;0.206]	0.462	Yes
EE	-0.258	[-0.344;0.377]	0.150	Yes
PE	-0.167	[-0.191;0.190]	0.078	Yes
SI	-0.105	[-0.201;0.236]	0.306	Yes
HM	-0.017	[-0.185;0.182]	0.846	Yes

Table 34 and Table 35 respectively summarize the estimation results for permutation test and PLS-MGA. Not surprisingly, the results for both methods are almost identical. All main relationships in the model are significant for both groups, except the relationship between effort expectancy (EE) and behavioral intention (BI) which is not significant for scenario 1. Therefore, it can be assumed that effort expectancy (EE) only influences behavioral intention (BI) of the users to use in-store ubiquitous computing-based services for alternative evaluation. Hence, the hypothesis H1.3 is accepted. Concerning the relationships of performance expectancy (PE) and social influence (SI) with behavioral intention (BI), no significant difference between two scenarios can be observed. Therefore, hypotheses H2.3 and H3.3 are rejected. However, the influence of hedonic motivation on behavior intention is significantly stronger for group 1. Therefore, the hypothesis H4.3 is accepted.

Table 34: Permutation test results for service type

Relationship	Service groups	Path coefficient	Standard error	t-Value (≥1.65)	Group1 vs. Group 2			
					Path coefficients -diff	95% confidence interval	p-Value	Significant level
EE→BI	Group 1: information search	0.054	0.039	1.380	Group 1 ns	n/a	n/a	n/a
	Group 2: alternative evaluation	0.123	0.034	3.668				
PE→BI	Group 1: information search	0.549	0.048	11.435	-0.096	[-0.145;0.150]	0.197	ns
	Group 2: alternative evaluation	0.646	0.057	11.276				
SI→BI	Group 1: information search	0.105	0.44	2.408	0.011	[-0.117;0.122]	0.868	ns
	Group 2: alternative evaluation	0.095	0.47	2.012				
HM→BI	Group 1: information search	0.288	0.048	5.997	0.158	[-0.153;0.140]	0.037	**
	Group 2: alternative evaluation	0.130	0.059	2.220				

Note: n/a = not applicable. ns = non-significant. *p <.10. **p <.05. ***p <.01.

Table 35: PLS-MGA results for service type

Relationship	Service groups	Path coefficient	Standard error	t-Value (≥1.65)	Group1 vs. Group 2		
					| Path coefficients -diff |	p-Value	Significant level
EE→BI	Group 1: information search	0.054	0.039	1.380	Group 1 ns	n/a	n/a
	Group 2: alternative evaluation	0.123	0.034	3.668			
PE→BI	Group 1: information search	0.549	0.048	11.435	0.096	0.198	ns
	Group 2: alternative evaluation	0.646	0.057	11.276			
SI→BI	Group 1: information search	0.105	0.44	2.408	0.011	0.869	ns

	Group 2: alternative evaluation	0.095	0.47	2.012			
HM→BI	Group 1: information search	0.288	0.048	5.997	0.158	0.037	**
	Group 2: alternative evaluation	0.130	0.059	2.220			

Note: n/a = not applicable. ns = non-significant. *p <.10. **p <.05. ***p <.01.

5.2.4.4 Technology Type

To examine the influence of technology type, the aggregated dataset from scenario 1 and 2 is defined as group 1 (302 cases) representing the responses for store-owned devices and dataset from scenario 3 (302 cases) is defined as group 2 representing the responses for customer-owned mobile devices. Based on the MICOM results summarized in Table 36, it can be concluded that at least partial measurement invariance has been established for all given multi-item constructs. Thus multi group analysis can be conducted with confidence.

Table 36: Summary of MICOM results for technology type

MICOM Step 1				
Configural variance established? Yes				
MICOM Step 2				
Composite	**Correlation c**	**5% quantile of the empirical distribution of c_u**	**P Value**	**Compositional invariance established?**
BI	1.000	1.000	0.169	Yes
EE	1.000	1.000	0.611	Yes
PE	1.000	1.000	0.269	Yes
SI	1.000	0.998	0.747	Yes
HM	1.000	0.999	0.428	Yes
MICOM Step 3				
Composite	**Difference of the composite's mean value (= 0)**	**95% confidence interval**		**Equal mean values?**
BI	-0.294	[-0.166;0.156]		No
EE	-0.064	[-0.162;0.131]		Yes
PE	-0.484	[-0.165;0.150]		No

SI	-0.172	[-0.157;0.148]	No
HM	0.001	[-0158;0.156]	Yes
Composite	**Logarithm of the composite's variances ratio (= 0)**	**95% confidence interval**	**Equal variances?**
BI	0.130	[-0.247;0.247]	Yes
EE	-0.050	[-0.409;0.365]	Yes
PE	0.105	[-0.221;0.224]	Yes
SI	0.035	[-0.243;0.227]	Yes
HM	0.024	[-0.176;0.198]	Yes

Table 37 and Table 38 respectively summarize the results for permutation test and the PLS-MGA. As it can be seen, all main relationships in the model are significant for both groups, except the relationship between social influence (SI) and behavioral intention (BI) which is not significant for group 1. Therefore, it can be assumed that social influence (SI) only influences behavioral intention (BI) of the users to use their own mobile devices for in-store ubiquitous computing based services which is in contrast to the hypothesized relationship therefore the H3.4 is rejected. Only the relationship between the performance expectancy (PE) and behavioral intention (BI) significantly differ between two groups however not in the hypothesized direction. Hence none of the hypothesis formulated for the moderating effect of technology type could be confirmed.

Table 37: Permutation test results for technology type

Relationship	Service groups	Path coefficient	Standard error	t-Value (≥1.65)	Group1 vs. Group 2			
					Path coefficients -diff	95% confidence interval	p-Value	Significant level
EE→BI	Group 1: stationary	0.106	0.033	3.223	-0.010	[-0.092;0.085]	0.824	ns
	Group 2: mobile	0.117	0.035	3.358				
PE→BI	Group 1: stationary	0.673	0.047	14.347	0.109	[-0.115;0.120]	0.078	*

	Group 2: mobile	0.563	0.045	12.383				
SI→BI	Group 1: stationary	0.056	0.039	1.426	Group 1 ns	n/a	n/a	n/a
	Group 2: mobile	0.142	0.042	3.371				
HM→BI	Group 1: stationary	0.180	0.052	3.494	-0.018	[-0.133;0.134]	0.785	ns
	Group 2: mobile	0.198	0.046	4.280				

Note: n/a = not applicable. ns = non-significant. *p <.10. **p <.05. ***p <.01.

Table 38: PLS-MGA results for technology type

Relationship	Technology groups	Path coefficient	Standard error	t-Value (≥1.65)	Group1 vs. Group 2		
					| Path coefficients -diff |	p-Value	Significant level
EE→BI	Group 1: stationary	0.106	0.033	3.223	0.010	0.585	ns
	Group 2: mobile	0.117	0.035	3.358			
PE→BI	Group 1: stationary	0.673	0.047	14.347	0.109	0.046	**
	Group 2: mobile	0.563	0.045	12.383			
SI→BI	Group 1: stationary	0.056	0.039	1.426	Group 1 ns	n/a	n/a
	Group 2: mobile	0.142	0.042	3.371			
HM→BI	Group 1: stationary	0.180	0.052	3.494	0.018	0.603	ns
	Group 2: mobile	0.198	0.046	4.280			

Note: n/a = not applicable. ns = non-significant. *p <.10. **p <.05. ***p <.01.

5.2.5 Summary of Empirical Results

Table 39 offers a summary of the empirical results. The conceptual model of the study consist of 30 hypotheses from which 14 hypotheses are concerned with direct relationships between dependent and independent variables whereas 16 are dedicated to moderator effects. Thereby 13 from 14 hypotheses formulated in the acceptance model of in-store ubiquitous computing-based information services are confirmed. Explicitly all of the hypotheses regarding the relationships between the belief system and behavioral intention to use as well as those regarding the relationships between the personal innovativeness and involvement (importance and personal relevance) and the cognitive factors in belief system are confirmed.

In addition, five out of six hypotheses formulated for the effects of the Internet dependency dimensions on the belief system are confirmed. Only one hypothesis on the influence of interaction orientation on effort expectancy is not supported by empirical data and therefore is rejected. The results concerning the moderating effects are less satisfactory. Only three out of 16 hypotheses can be supported by empirical data.

Table 39: Summery of hypotheses testing

Hypothesis	Relationship	Empirical testing
H1	Effort expectancy has a significant positive effect on behavior intention to use in-store ubiquitous computing-based information services	✔
H1.1	The influence of effort expectancy on behavior intention will be moderated by age such that the effect will be stronger for older people than younger people	✘
H1.2	The influence of effort expectancy on behavior intention will be moderated by gender such that the effect will be stronger for women than for men	✘
H1.3	The influence of effort expectancy on behavior intention will be moderated by service type such that the effect will be stronger for services assisting alternative evaluation stage	✔
H1.4	The influence of effort expectancy on behavior intention will be moderated by technology type such that the effect will be stronger for store-owned devices.	✘
H2	Performance expectancy has a significant positive effect on behavior intention to use in-store ubiquitous computing-based information services.	✔
H2.1	The influence of performance expectancy on behavior intention will be moderated by age such that the effect will be stronger for younger people than older people	✘
H2.2	The influence of performance expectancy on behavior intention will be	✘

Hypothesis	Relationship	Empirical testing
	moderated by gender such that the effect will be stronger for men than for women	
H2.3	The influence of performance expectancy on behavior intention will be moderated by service type such that the effect will be stronger for services assisting information search stage	✘
H2.4	H2.4: The influence of performance expectancy on behavior intention will be moderated by technology type such that the effect will be stronger for user-owned mobile devices.	✘
H3	Social influence has a significant positive effect on behavior intention to use in-store ubiquitous computing-based information services.	✔
H3.1	The influence of social influence on behavior intention will be moderated by age such that the effect will be stronger for older people than younger people	✘
H3.2	The influence of social influence on behavior intention will be moderated by gender such that the effect will be stronger for women than for men	✘
H3.3	The influence of social influence on behavior intention will be moderated by service type such that the effect will be stronger for services assisting information search stage	✘
H3.4	The influence of social influence on behavior intention will be moderated by technology type such that the effect will be stronger for store-owned devices.	✘
H4	Hedonic motivation has a significant positive effect on behavior intention to use in-store ubiquitous computing-based information services.	✔
H4.1	The influence of hedonic motivation on behavior intention will be moderated by age such that the effect will be stronger for younger people than older people	✔
H4.2	The influence of hedonic motivation on behavior intention will be moderated by gender such that the effect will be stronger for men than for women	✘
H4.3	The influence of hedonic motivation on behavior intention will be moderated by service type such that the effect will be stronger for services assisting information search stage	✔
H4.4	The influence of hedonic motivation on behavior intention will be moderated by technology type such that the effect will be stronger for store-owned devices.	✘
H5	Behavior intention to use in-store ubiquitous computing-based information services has a significant positive effect on customers' preference of stores offering such services.	✔
H6	Action orientation dependency of customers on the Internet has a significant positive effect on effort expectancy of in-store ubiquitous computing-based information services.	✔
H7	Action orientation dependency of customers on the Internet has a significant positive effect on performance expectancy of in-store ubiquitous computing-based information services.	✔
H8	Interaction orientation dependency of consumers on the Internet has a significant positive effect on effort expectancy of in-store ubiquitous	✘

Hypothesis	Relationship	Empirical testing
	computing-based information services.	
H9	Interaction orientation dependency of consumers on the Internet has a significant positive effect on performance expectancy of in-store ubiquitous computing-based information services.	✔
H10	Social play dependency of customers on the Internet has a significant positive effect on hedonic motivation of in-store ubiquitous computing-based information services	✔
H11	Solitary play dependency of customers on the Internet has a significant positive effect on hedonic motivation of in-store ubiquitous computing-based information services	✔
H12	Personal innovativeness in IT has a significant positive effect on effort expectancy of in-store ubiquitous computing-based information services.	✔
H13	Personal relevance of making an informed decision has a significant positive effect on performance expectancy of in-store ubiquitous computing-based information services.	✔
H14	Importance of having shopping assistance has a significant positive effect on performance expectancy of in-store ubiquitous computing-based information services.	✔

6 Discussion of Results and Conclusion

6.1 Theoretical Implications

To draw a sound conclusion from the empirical results and outline the theoretical contribution of this study, first empirical results are discussed and interpreted. At this point, the focus is mainly on unexpected results and rejected hypotheses. Next, the theoretical findings are summarized, highlighting the main contributions of this dissertation to theoretical knowledge.

Performance expectancy, effort expectancy, social influence, and hedonic motivation significantly influence behavioral intention to use in-store ubiquitous computing-based information technologies. Overall, the empirical results support the applicability and validity of UTAUT2 as a base model to predict the behavioral intention of customers to use ubiquitous computing-based technologies. Thus, this study satisfies the call for testing UTAUT2 in different technology contexts (Venkatesh et al., 2012) and extends its generalizability to in-store ubiquitous computing-based information technologies.

Having a closer look into the results, performance expectancy is by far the most important driver of behavioral intention. Hedonic motivation is as well a significant determinant of behavioral intention but it can only take the second place with a relatively smaller effect size than performance expectancy. Previous studies in the context of in-store technologies report inconsistent results regarding the importance of hedonic motivation. Whereas Spreer and Kallweit (2014), aligned with the original UTAUT2 paper, report hedonic motivation to be the more important driver of behavioral intention than performance expectancy, Rothensee (2010) reports the vice versa. The former study is using a fully functional prototype in a real shop while the later one uses a movie to describe the given technologies to the participants. Thus, one could argue that the study methods are responsible for the contradictory results. That is without any direct experience with a given technology, it is more difficult for participants to evaluate its emotional benefits. This argument could be valid for the current results since a scenario-based study does also build on participants' indirect experiences. However, the difference between the effects of performance expectancy and hedonic motivation on behavioral intention in this study is too substantial to be associated to the method bias. Therefore, based on the current results, it can be concluded that in-store ubiquitous computing-based information technologies are above all decision-support agents that are valued by their contribution to more efficient purchase decisions and thus, their functional benefits are much more important than hedonic aspects.

Based on the empirical results, social influence after effort expectancy is the most unimportant driver of behavior intention to use in-store ubiquitous computing-based information services. Consistent with previous research, the rather small effect of effort expectancy on behavioral intention was already expected. Current empirical results confirm that the participants in general do perceive in-store technologies easy to use, which is aligned with the design philosophy of ubiquitous computing technologies. Previous research shows that if the technology is inherently relatively easy to us, effort expectancy will have less impact on individuals' technology use decision (Subramanian, 1994; Yousafzai et al., 2007a). That is the users don't see the ease of use as a system quality but rather take it for granted. However, the minor impact of social influence on behavior intention is rather surprising. A possible explanation is that the prediction of expectation and opinions of important others prior to the existence of a technology is principally difficult. In this study, participants have to gauge the reaction of their social environment associated with them using a technology that yet does not exist.

Contrary to expectations, gender does not show salient moderating effect on base model relationships. Explicitly, none of hypotheses concerning the moderating effect of gender can be supported by the empirical data. Two possible reasons can be responsible for the absence of any significant difference in perceptions of male and female participants, namely shrinking gender gap (Leopold et al., 2016) and ever-increasing penetration of information technologies in developed societies. Since gender decision making differences are rather culture-induced than biological (Bem, 1981; Brosnan, 1998; Brosnan and Davidson, 1996; Lynott and McCandless, 2000), it is rational to expect that by shrinking gender divide, the gender related differences in technology perceptions do as well vanish. Furthermore, several studies show that the gender differences in technology perception and acceptance is diminishing as technologies are becoming more pervasive (Faqih and Jaradat, 2015; Lip-Sam and Hock-Eam, 2011; Serenko et al., 2006; Zhou et al., 2007). Thus, it can be argued that in the current social and technological landscape, gender does not result in variations in individuals' perceptions regarding in-store ubiquitous computing-based information services and thus their willingness to use such services.

Regarding the moderating effect of age, only one hypothesis indicating moderating effect of age on the relationship between hedonic motivation and behavior intention could be supported since this relationship is only significant for the younger age group. The results for effort and performance expectancy are quite surprising. The relationship between effort expectancy and behavior intention is only significant for the younger age group and the relationship between performance expectancy and behavior intention is significantly stronger for the older age group stating exactly the opposite of hypothesized effects. In addition, performance expectancy is the only determinant of behavior intention for the older age group. Based on these findings, it can be argued that since other beliefs of the given technology has no effect on the older age group's decision to use that technology, its utilitarian value becomes even more salient for the usage decision. Therefore performance expectancy is a stronger driver of intention behavior for the older age group. However this discrepancy with previous research might also be caused by the sample characteristics, most notably the sample size. Analyzing the moderator effects, the total sample is split along age lines resulting in subgroups with rather small sample sizes. Additionally the sample sizes for the age groups are quite unbalanced, 227 cases for younger group and 75 cases for older group. Several relationships that are statistically significant in total sample turn out to be not significant in subgroups. Therefore a well-founded conclusion in this regard requires additional research.

Two out of four hypotheses regarding the moderating effect of service type are supported by empirical results. The effect of effort expectancy on behavior intention is only significant for services supporting the alternative evaluation stage. Consistent with the corresponding hypothesis, this finding indicates that the perceived ease associated with the use of in-store ubiquitous computing-based services only influences the usage decision when the technology is used to perform more complex tasks as alternative evaluation. Based on this finding, it can be suggested that it is the overlooked effect of task complexity in previous research which is responsible for inconsistent results for the effect of effort expectancy on behavior intention, positive significant effect (Kurkovsky and Harihar, 2006; Kwon et al., 2007; Lee et al., 2011; Weijters et al., 2007) versus no effect (Kowatsch and Maass, 2010; Müller-Seitz et al., 2009; Rothensee, 2010; Spreer and Kallweit, 2014). Furthermore, as hypothesized, the effect of hedonic motivation on behavior intention is significantly stronger for services assisting the information search stage. However, contrary to hypothesized effects, the impacts of performance expectancy and social influence on behavior intention do not significantly differ between information search and alternative evaluation services. It can be argued that in-store ubiquitous computing-based information technologies facilitate the alternative evaluation task to an extent which mitigates the negative effect of task complexity on perceived usefulness. Therefore the relative importance of utilitarian benefits of in-store ubiquitous computing-based information technologies remains unchanged for information search and alternative evaluation services. In regard to the non-existence moderator effect of service type on the relationship between social influence and behavior intention, a possible explanation can be that since both services for information search and alternative evaluation stages are offered in a single technology artifact, individuals' may evaluate the opinions of important others for the technology as a whole regardless of complexity of the task for which they use the technology.

None of hypotheses regarding the moderator effect of technology type can be supported by the empirical data. The impacts of effort expectancy and hedonic motivation on behavior intention do not significantly differ between the stationary and mobile technologies. Regarding effort expectancy, contrary to expectations, individuals' skill and experience with mobile devices do not significantly change their perception about ease of using in-store ubiquitous computing-based information services which are offered on their own devices. On one hand, as expected, empirical results show that individuals perceive services based on their own mobile devices easier to use than those offered in store-owned devices. On the other hand, regardless of the type of the technology, participants perceive in-store ubiquitous computing-based technologies relatively easy to use and put relatively low weight on their easiness feature while making the usage decision. Referring to previous literature, above, it is argued that this is because, in accordance with the design philosophy of ubiquitous computing technologies, in-store ubiquitous computing-based information technologies are inherently easy to use. Thus, however individuals' skill and experience with mobile devices leads to a more positive effort expectancy belief regarding services offered in mobile devices, the difference is too marginal to significantly change the relative importance of effort expectancy on behavior intention for services offered on customer owned mobile devices versus store owned stationary devices. Similarly, the results from parametric test show no significant difference induced by type of the technology for the effect of hedonic motivation on behavior intention. The corresponding hypothesis is inferred from the reasoning that the experience with mobile devices reduces the perceived novelty appeal of in-store services which are offered on customers' own devices. Thus, the perceived novelty which contributes to the effect of hedonic motivation on behavior intention is hypothesized to be weaker for in-store services offered on customer owned mobile devices than those offered on store-owned devices. Failing to confirm this hypothesis, it can be suggested that individuals perceive the novelty of services offered on their own mobile devices as attractive as those offered on store-owned devices. A possible reason can be that as in-store ubiquitous computing-based information technologies are yet future technologies and inherently novel, participants experience with mobile devices does affect their novelty appeal.

The hypotheses concerning the moderator effects of technology type on relationships between social influence and performance expectancy on behavior intention are as well rejected. However, the parametric tests show that the strength of these relationships differ by the type of technology but in the opposite direction of the hypothesized effects. Contrary to the hypothesis, the relationship between social influence and behavior intention is non-significant for store-based devices whereas it is significant for customer owned mobile devices. Above, while discussing about the relatively weak effect of social influence on behavior intention in aggregated data, it is argued that the prediction of expectation and opinions of important others prior to the existence of a technology is principally difficult. Having a significant relationship between social influence and behavior intention only for mobile technologies strengthens the validity of this argument. Referring to the same argument, since the mobile devices already exist, participants could gauge the reaction of their social environment associated with them using in-store ubiquitous computing-based services offered on their own mobile devices better than those offered on store-based devices. Regarding the relationship between performance expectancy and behavior intention, contrary to the hypothesis, the relationship is significantly stronger for store owned stationary devices than customer owned mobile devices. As expected, empirical results show that participants perceive services offered on their own mobile devices more useful than those offered on store owned stationary devices. However, it doesn't translate to the stronger effect of performance expectancy on behavior intention. A possible reason for this finding can be the mitigating effect of perceived privacy concerns on perceived usefulness of services offered on user owned mobile devices. Previous research, in other technology domains, show that with increasing perceived privacy concerns the value of utilitarian advantages of the technology decreases (McGoldrick, 2001; Ziesak, 2013). In-store ubiquitous computing information technologies are designed to offer personalized services to their users for which user information is essential. In this study, in the scenario designed for store owned stationary devices (smart mirror scenario), the required information for service delivery is limited to customers' actions in the store and is not coupled with users' personal information. However to use in-store information services in mobile devices, users need to download an application in their own mobile devices which automatically shares some user information with the provider and extends the potential range of accessibility to outside of the store. Therefore, the perceived privacy concerns about the collection of personal information and unauthorized secondary use might be the barrier for willingness to use in-store services offered on user owned mobile devices.

Except the relationship between interaction orientation and effort expectancy, all relationships hypothesizing the effects of user characteristics on belief system are supported by empirical data. Thus as hypothesized, the empirical result show that user characteristics as Internet dependency relations, personal innovativeness, and involvement influence various beliefs of individuals' concerning in-store ubiquitous computing-based information services.

Based on the above mentioned discussions, this study provides strong contributions to theoretical knowledge. These contributions can be summarized in four categories:

The first contribution is made by extending existing knowledge in technology acceptance into a new context. A context-specific model for the acceptance of the in-store ubiquitous computing-based information services is developed. UTAUT2 is modified for in-store ubiquitous computing-based information services context and extended by germane user, service, and technology characteristics. The model is the most extensive model ever developed in this context. The study provides empirical support for the comprehensive acceptance model of in-store ubiquitous computing-based information services. In addition, this study satisfies the call for testing UTAUT2 in different technology contexts (Venkatesh et al., 2012) and extends its generalizability to in-store ubiquitous computing-based information technologies. The contextual model explains 85% of the variance in behavioral intention to use in-store ubiquitous computing-based information services which is considerably high in acceptance studies in general and such studies in the context of in-store technologies in particular. In the original UTAUT2 paper, the model could only explain 44 % of the variance in behavioral intention and the highest explained variance for behavioral intention among the reviewed studies in the context of in-store technologies was 71% (Rothensee, 2010).

Considering the general gap in technology acceptance research (Venkatesh et al., 2003), the second contribution resolves the gap in knowledge regarding the link between user acceptance and desired usage outcome. The study identifies intention to prefer as an important positive outcome of behavior intention. Incorporating intention to prefer into the model also increases the practical relevance of the developed model. Behavior intention to use in-store ubiquitous computing-based services explains 60% of variance in intention to prefer. That is the intention to use in-store ubiquitous computing services strongly predicts the intention to prefer stores offering those services.

The third contribution is made by incorporating individual differences into the acceptance model of in-store ubiquitous computing-based information technologies. First, a theory of how prior Internet experience drives the acceptance of in-store ubiquitous computing-based information technologies through its influence on beliefs about the technology is posited and supported by empirical data. By doing, new Internet dependency constructs are introduced into the technology acceptance model. It is postulated that media dependency theory offers the best proxy for conceptualization of individuals' favorable attitude towards Internet. This study manifests the feasibility of viewing the favorable attitude development process towards Internet as the process of dependency relations formation on information resources of Internet. Consequently this study shows that media dependency theory provides a rich theoretical foundation for identifying the salient effects of Internet information use and consequently their influences on beliefs about new but similar information technologies. In addition, this study satisfies the call for developing and applying more detailed and domain specific conceptualization of experience in technology acceptance studies (Sun and Zhang, 2006). Second two previously defined constructs, namely personal innovativeness in IT and involvement are identified as additional important factors driving the positive belief formation in the given context. The hypothesized relationships are supported by empirical data. Furthermore, the findings indicate that in the context of in-store ubiquitous computing-based information technologies, the extent of importance and relevance, two different facets of the notion of involvement, differs for an individual. Consequently this study delivers evidence that decomposing the involvement factor into two factors of relevance and importance results in a better understanding of effects of involvement on beliefs formation. Through the antecedent factors of beliefs, the proposed model can explain 31% variance in performance expectancy, 31% of variance in effort expectancy, and 19% of variance in hedonic motivation. In user acceptance studies, the R^2 values of 0.4 and 0.5 for behavior intention and use are considered as substantial (Venkatesh et al., 2012). However for customers' beliefs about the technology as effort expectancy, performance expectancy and hedonic motivation, the R^2 values above 0.3 are rarely observed (Agarwal and Prasad, 1999; Lu et al., 2005; Venkatesh and Bala, 2008). Therefore, the obtained R^2 values for the current model are considered rather high.

The forth contribution to new knowledge is the evidence for generalizability of the developed model across different in-store ubiquitous computing-based information technologies and services. One of the objectives of this dissertation is to develop an acceptance model applicable for entire range of in-store ubiquitous computing-based applications. Therefore, the model is tested for three different scenarios each representing certain technology or service type. The scenario comparisons in this study indicate that the proposed model performs about equally well across different technology and service types. The explained variances in behavioral intention for the information search stage (scenario 1), alternative evaluation stage (scenario 2), store owned stationary devices (aggregated scenario 1 and 2), and customer owned mobile devices (scenario 3) are respectively 75%, 75%, 82%, 74%. At the same time, however, empirical results regarding previously unidentified moderator effects of technology type and service type on the base model relationships shows differences in path coefficients in some of the relationships. Although except for two incidents, the observed path coefficient differences are inconsistent with the previously stated hypotheses; the implications of these contradictory findings raise at least two important theoretical issues. First, complexity of the task supported by a technology might be responsible for the inconsistent results for the effect of effort expectancy on behavior intention, positive significant effect (Kurkovsky and Harihar, 2006; Kwon et al., 2007; Lee et al., 2011; Weijters et al., 2007) versus no effect (Kowatsch and Maass, 2010; Müller-Seitz et al., 2009; Rothensee, 2010; Spreer and Kallweit, 2014). Second, for the technologies which extend the potential range of customer data accessibility to outside of the store, as customers' mobile devices, perceived privacy concerns might mitigate the value of utilitarian advantages. By and large, the proposed model enables a reasonably accurate prediction of the applications of ubiquitous computing technologies in the retail context.

6.2 Managerial Implications

To this point, through the empirical analysis, mainly the relative importance of individuals' perceptions and characteristics to determine the behavioral intention and intention to prefer is examined. The importance of these determinants is gauged by the value of estimates of path model relationships. The results provide insights into how individuals evaluate and form intentions to use ubiquitous computing-based information systems in retail stores. From a managerial point of view, however, the more important issues are

- how managers can utilize these findings to make interventions that can result in a greater acceptance and successful introduction of such technologies in stores.
- and how they can harvest the acceptance and use of such technologies to gain competitive advantage.

As discussed in the method choice section, one of the features of the PLS-SEM method is the extraction of the latent variable scores (Hair et al., 2014a; Völckner et al., 2010). That is in addition to the relative importance of constructs in the structural model the average values of latent variable scores representing their actual performance can be calculated enabling the importance-performance matrix analysis (IPMA) (Hair et al., 2014a). IPMA allows the identification and thus prioritization of the most important areas for management actions to provide pertinent managerial recommendations from the empirical results.

Thus, to translate the empirical results into managerial actions, first important-performance analysis of the path modeling results is conducted. Next, the findings are synthesized to derive managerial recommendations for brick and mortar retail in terms of design, choice, and introduction strategies of in-store ubiquitous computing-based information systems.

From the managerial point of view, increasing the store preference and customers' return rate is the ultimate goal to implement ubiquitous computing-based technologies in stores. Therefore, intention to prefer is chosen as the target construct for the importance-performance analysis. To provide a more comprehensive results the IPMA are conducted in scenario level.

Figure 32 shows the importance-performance matrices for information search and alternative evaluation services. The importance of each variable emerges from its total effects on intention to prefer, whereas the performance is determined by calculating the average values of each exogenous variable on a scale from zero (lowest performance) to 100 (highest performance).

As mangers’ resources are always limited, it is important to first devote these resources on areas holding higher priorities. Thus, having the importance-performance matrices, the next step is the priority assignment to management-oriented actions. The common practice here is to focus on exogenous variables with relatively high importance and relatively low performance values. The rationale behind this approach is that first, these variables hold a relatively high performance improvement potential and second because of their high importance level one unit improvement in their performance results in rather sizeable improvement in the performance of the target construct (Hair et al., 2014a; Ringle et al., 2016).

The theoretical model of this work consists of two distinct groups of variables, namely variables representing individuals’ perceptions concerning the given technology (e.g. effort and performance expectancy) and variables projecting various user characteristics (e.g. personal relevance and action orientation). Individuals’ technology perception variables reveal which technology features and to what extent are important for users’ store preference. Thus from managerial point of view, analyzing their importance and performance can guide the technology design and communication strategy development. Retail managers can take actions to improve the performance level of these variables for example improving customers’ performance expectancy perception about the given technology by communicating and highlighting its functional advantages. Thus the focus of management-oriented actions should be on variables with relatively high importance and relatively low performance values.

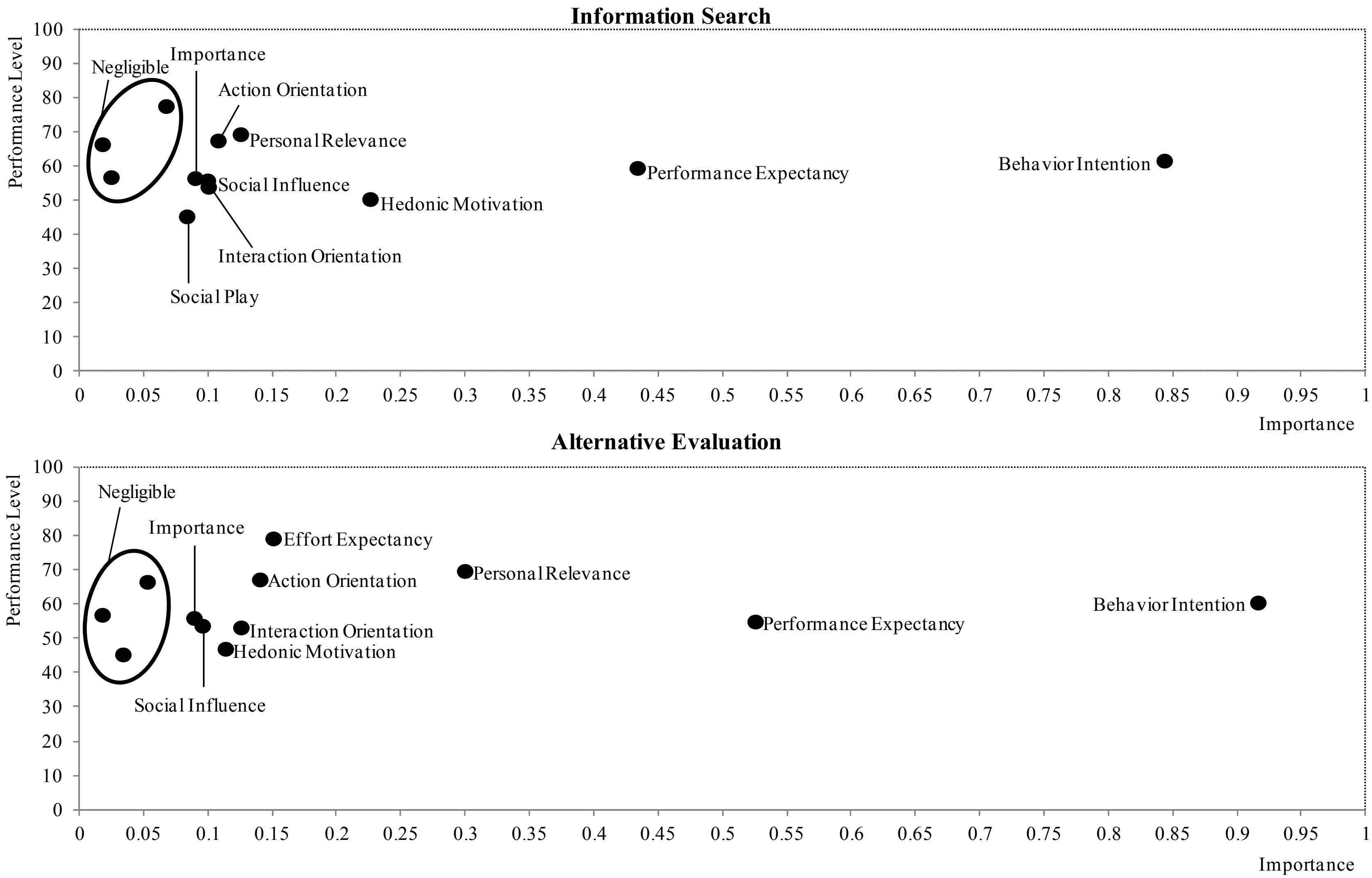


Figure 32: Importance-performance matrix analysis for determinants of intention to prefer (information search and alternative evaluation

In contrast, for user characteristics variables, it is not feasible for retail managers to improve the performance level of these variables for example increasing the extent to which users are dependent on the Internet information. These variables however can provide managers with whom and how to target for successful introduction of ubiquitous computing-based information services. Therefore, regarding user characteristic variables, the most important areas of management-oriented actions are identified by focusing on variables with relatively strong impact on intention to prefer and at the same time relatively high performance level. Relatively high importance level indicates that the users with the given characteristic are comparatively more inclined to prefer stores offering ubiquitous computing-based information services. Relatively high performance level indicates the popularity of these characteristics. Here the goal is not to identify technology features whose performance improvement result in a greater store preference but to identify the users who are more inclined to prefer the stores which offer ubiquitous computing-based information and therefore crucial for successful introduction of in-store ubiquitous computing-based information technologies. For the sake of simplicity, henceforth the first group of variables (technology perceptions) is referred to as controllable variables and the second group (user characteristics) as uncontrollable variables.

Regarding controllable variables in information search services, it becomes apparent that because of its major impact, behavior intention is highly relevant for increasing the customers store preference. At the same time due to its intermediate performance level, there is relatively high improvement potential. Therefore, this factor should be assigned the highest priority while developing management-oriented measures. Nearly the same applies to importance and performance in the performance expectancy. Thus, management measures should to be taken to improve the performance expectancy of customers. In comparison to performance expectancy and behavior intention, hedonic motivation exert lower impact on store preference but at the same time it offers the major improvement potential in terms of performance level. Social influence has relatively low impact and therefore is of less importance and low priority for activities aimed at increasing customers store preference. Concerning alternative evaluation services, similar to information search services, management efforts should be directed to improve performance levels of behavior intention, performance expectancy, and hedonic motivation. However, unlike information search services, the impact of effort expectancy is not negligible for alternative evaluation services. Effort expectancy has the highest performance value so that there is a relatively minor potential for further performance improvement. In addition its impact on intention to prefer is relatively low therefore even an increase in performance value cannot considerably change customers' store preference. Therefore although future maintenance of the performance level should be ensured, extra investment for its improvement is not recommended.

Comparing the IPMA results of information search and alternative evaluation services, the performance level of behavior intention to use information search services is about as good as the one for alternative evaluation services. However, its total effects on intention to prefer is relatively higher in alternative evaluation services than information search services. That is customers' intention to use in-store ubiquitous computing-based information technologies for alternative evaluation increases customers' store preference and thus loyalty more than their intention to use the given technologies for information search. As a result, successful implementation of management measures for improvement of performance level of intention to use alternative evaluation services will lead to a higher store preference. From managerial point of view, increasing the store preference and customers' return rate is the ultimate goal to implement ubiquitous computing technologies in stores. Therefore, as both services are often offered based on the single technology artifact, it is more effective to direct the focus of management activities on alternative evaluation services.

Regarding uncontrollable factors, personal relevance is the most relevant factor for managerial actions in alternative evaluation services with both highest impact on behavior intention and highest performance value indicating the individuals' high dedication and interest to make informed purchasing decisions. Action orientation, interaction orientation, and importance are respectively of high relevance for activities targeting populations of user that are more inclined to use the new services. Therefore these factors are important to consider while developing a strategy for introduction of in-store ubiquitous computing-based information services. The rest of the user characteristics have too small impact on store preference to be relevant for managerial-oriented activities.

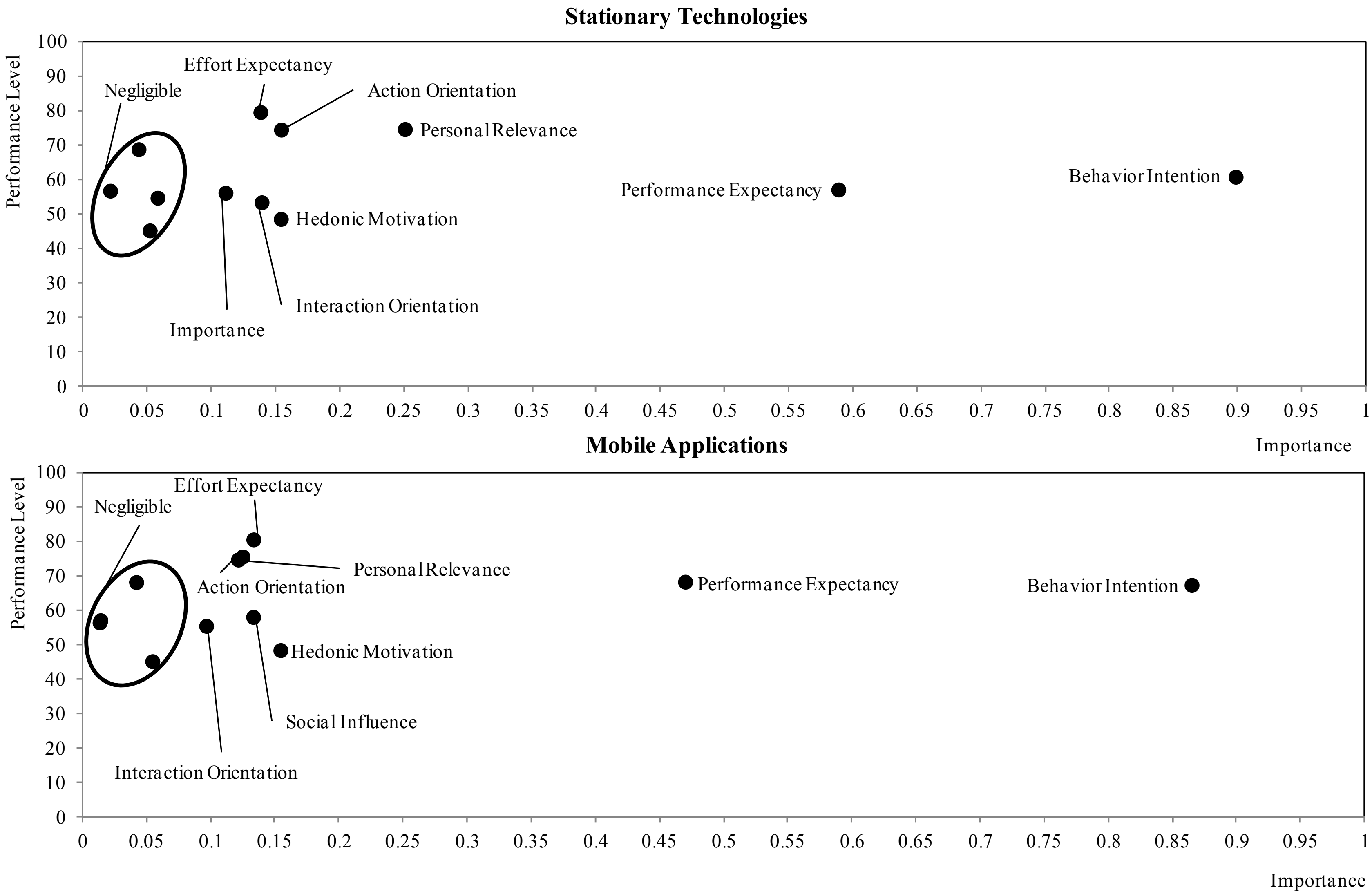


Figure 33: Importance-performance matrix analysis for determinants of intention to prefer (stationary technologies and mobile applications)

Figure 33 shows the importance-performance matrices for stationary technologies and mobile applications. Regarding controllable variables in stationary technologies, it becomes apparent that because of its major impact, behavior intention is highly relevant for increasing the customers store preference. At the same time due to its intermediate performance level, there is relatively high improvement potential. Therefore, this factor should be assigned the highest priority while developing management-oriented measures. Nearly the same applies to importance and performance in the performance expectancy. Thus, management measures should to be taken to improve the performance expectancy. In comparison to performance expectancy and behavior intention, hedonic motivation exerts lower impact on store preference but at the same time it offers the major improvement potential in terms of performance level. Effort expectancy has the highest performance value so that there is a relatively minor potential for a further performance improvement. In addition its impact on intention to prefer is relatively low therefore even an increase in performance value cannot considerably change customers' store preference. Therefore although future maintenance of the performance level should be ensured, extra investment for its improvement is not recommended.

Concerning mobile applications, similar to stationary technologies, management efforts should be directed to improve performance levels of behavior intention, performance expectancy, and hedonic motivation and to maintain performance level of effort expectancy. However, unlike stationary technologies, the impact of social influence is not negligible for mobile applications. In comparison to behavior intention, performance expectancy and hedonic motivation, social influence has lower impact on store preference. At the same time it holds a higher performance level than hedonic motivation therefore it should be assigned a lower priority for management oriented activities.

Comparing the IPMA results for stationary technologies and mobile applications, it becomes apparent that no matter which technology retailers choose to implement, they have to focus their managerial actions on improving customers' behavior intention, performance expectancy, and hedonic motivation. In addition as the importance and performance level of behavior intention as the most relevant factor for increasing store preference are almost identical, it can be concluded that both technologies are equally good to increase the store preference.

Regarding uncontrollable factors, personal relevance and action orientation are the most relevant areas for managerial actions for both stationary technologies and mobile applications. Managerial efforts should be directed to reach to customers who are more dedicated to make informed purchasing decisions as well as the ones who are dependent on Internet information resources to take purchasing decisions. Interaction orientation and importance are less important with importance being negligible for store preference in mobile applications. The rest of the user characteristics have too small impact on store preference to be relevant for managerial-oriented activities.

Synthesizing the above mentioned IPMA results, major practical insights in terms of design, promotion and choice can be derived. These insights are discussed and formulated as recommendations for managerial actions. As in-store ubiquitous computing based information services are not widely spread, following Venkatesh and Bala (2008) recommendation, the focus here is on preimplementation intervention strategies.

Overall the results of this study show that in-store ubiquitous computing-based information services are able to increase customers' store preference. This finding should be quite encouraging to brick and mortar stores. Independent from the service and technology type, this preference depends considerably on customer's intention to use and perceived usefulness of services. Therefore managerial measures should assign the highest priority to increase the performance level of these factors. Thus before introducing in-store ubiquitous computing-based information services, these two factors should be emphasized in design and promotion. In terms of promotion, it can be done by informing customers about different areas of applications and their potential to improve shopping performance. For example by contrasting people making fast and confident purchase decisions using in-store ubiquitous computing-based information services with people waiting for service employees to require a piece of information. Here, stressing the ease of making an informed decision for example by emphasizing the availability of the detailed and customized product information and product comparison assistance can be especially appealing for customers who are more dedicated in making informed purchase decisions. While developing the promotion strategies, the beneficial aspects of alternative evaluation services should be in foreground as even a minor improvement in performance expectancy of services supporting alternative evaluation will have a substantial effect on store preference. In addition, promotional programs can be designed to stimulate customers' intention to use above and beyond influencing their technology perceptions. For example, offering special discounts on products which can be only used through given technologies. Once customers use the system, it would be easier for them to recognize and acknowledge its beneficial impact. In terms of design, the efforts should be directed at ensuring and improving service delivery speed and reliability.

Furthermore measures to improve the performance level of hedonic motivation and maintaining that of effort expectancy need to be incorporated into design and promotion strategies. Hedonic motivation is especially relevant for information search services. Therefore it is recommended to first focus on improving the fun and novelty aspects of services supporting customers' information search. In terms of promotion, this could be emphasized by highlighting the interactive characteristic of such technologies (Brave and Nass, 2003; Huang, 2003; Rothensee, 2010). In terms of design this could be done for example through integrating multimedia modalities (graphic, voice, video) or human like characteristics as faces and emotion manifestation in the system (Huang, 2003; Rothensee, 2010). To maintain the performance level of effort expectancy, efforts should be directed at ensuring the design of user friendly service options with intuitive user interfaces.

In addition, managerial measures should be taken to reach customers who are dependent on Internet information resources to make purchase decision and to interact with others. Due to ever-increasing trend of online medium penetration in different facets of our lives, it can be argued that an organic increase in the performance level of Internet dependency relationships is to expect over time. Therefore considering Internet dependency constructs with relatively strong impact on store preference while developing promotional strategies would be vital for its successful implementation of in-store ubiquitous computing-based information services. Customers with relatively high action orientation dependency can be targeted by messages which help them to recall the positive experiences that they had with online medium in searching and evaluation of information and associate them with the functionalities of the in-store ubiquitous computing-based information services. These customers can be reached through Internet-based channels. Therefore it would be more effective to place such messages in for example social media platforms.

Last but not least, the results of this study provide an answer to which technology to choose. Services for information search and alternative evaluation offered by a stationary technology are replicable on consumers' own mobile devices. Comparing the IPMA results for stationary technologies and mobile applications, it becomes apparent that the importance and performance level of behavior intention as the most relevant factor for increasing store preference are almost identical. Based on these results, it can be suggested that both technologies are equally good in increasing store preference. As the level of investment in stationary systems is significantly higher than in mobile applications, it would be more cost-effective for retailers to provide in-store ubiquitous computing-based services on customers own devices.

6.3 Limitations and Recommendations for Future Research

Like any other research, this study has inevitable limitations inherited from its scope and analysis method which at the same time indicate avenues for future research.

One limitation originates in the scenario-based survey studies. In this study, the scenario development is based on the profound research on the existing real-world applications. In addition, various measures are taken to ensure that the developed scenarios are neutral and imitate a sufficient degree of real-world setting. However, it does not change the fact that a scenario does not produce a real-world application but only reflects one. Therefore, the participants' perceptions are dependent on their ability to put themselves in a hypothetical situation. As a result, it is possible that participants' perceptions of the ubiquitous computing-based information technologies have been biased by means of scenarios. It will be interesting for future research to replicate this study in real-world setting by conducting a prototype-based study, which allows participants to experience in-store ubiquitous computing-based information technologies in a first-hand manner. In addition, future research could be focused on replicating this study with a larger and more representative sample size particularly to test the effects of age and gender

To develop a parsimonious model, this study does not include constructs whose roles in shaping the acceptance in previous studies are either rejected or reported as minor. One of these constructs is privacy. The general research on acceptance of ubiquitous computing applications has pointed out the importance of privacy (Hoffmann et al., 2011), however based on the results of the studies in the area of in-store applications privacy beliefs play a very minor role in shaping the acceptance (Müller-Seitz et al., 2009; Rothensee, 2010). Yet privacy and data protection issues in digital age are gaining more importance and the individuals' awareness of privacy issues is rising. Thus, it will be sound for future research to reexamine the influence of perceived privacy on behavioral intention of using in-store ubiquitous computing-based information services.

Another aspect which is not included in the scope of this study but is worthwhile to examine is the impact of product category (e.g. more complex vs. less complex or more expensive vs. less expensive) on customers' willingness to use in-store ubiquitous computing-based information services. The complexity level of a product associated with the number of attributes and alternatives might influence the consumers' decision making process (Bettman et al., 1998; Swaminathan, 2003). That is the higher the number of features and alternatives in a product category, the greater the cognitive load (Payne et al., 1993). In-store ubiquitous computing-based information services assist customers through the information search and evaluation process reducing the cognitive effort, for example by organizing the product/s information based on the customer's most important attribute/s in a small and easy to read table. Thus, for instance, perceived benefit of in-store ubiquitous computing based services could be higher for more complex products. Future research might examine the effects of product categories on the belief-intention relationships of the current model.

Appendix

Questionnaire for the Use and Acceptance of Ubiquitous Technologies in Retail Environment

Thank you for taking the time to complete this survey, your feedback is very important to us.

This survey should only take about 20 minutes of your time. Any questions marked with an asterisk (*) require an answer in order to progress through the survey.

As a token of our appreciation for your participation in this important study, upon receipt of your completed questionnaire, you will be asked whether you would like to be entered in a

lottery in which respondents are eligible **to win 5, €25 gift certificates from Amazon.**

Here we want to ask you about your own opinion and individual estimations. There are no right or wrong answers. Therefore please answer the questions as spontaneously as possible.

If you have any questions about the survey, please contact us at sara.kheiravar@tuhh.de or call 040428784522

In order to progress through this survey, please use the following navigation buttons:

Click the Next button to continue to the next page.

Click the Submit button to submit your survey.

General Questions I

What is your gender?

( ) Male

( ) Female

What is your age?

___ Years old

Approximately, how old were you when you used Internet *for the first time*?

___ Years old

Smart Purchase Relevance

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewhat	Undecided	Agree Somewhat	Agree	Strongly Agree
It is important to me to feel like a smart shopper and to make successful purchases.							
It is important to me that the products I buy are consistent with my style.							
It is important for me to inform myself about the alternatives (e.g., price, quality) before making the purchase.							
When I am shopping, I am usually very careful with the decisions I make..							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

Importance

	Strongly disagree	Disagree	Disagree Some-what	Undecide d	Agree Some-what	Agree	Strongly Agree
I often have trouble choosing which item to buy when I am shopping.							
I often end up buying something that I don't need, because I get confused when I am shopping.							
I would like to have some assistance when I am shopping, especially when the product I need is expensive.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

Media dependency – Internet dependency

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
decide where to buy certain products/services.							
decide what to buy							
decide between alternative products/services							
plan for evening and weekend activities							
decide whether to buy a certain product/service or not.							

The scenarios

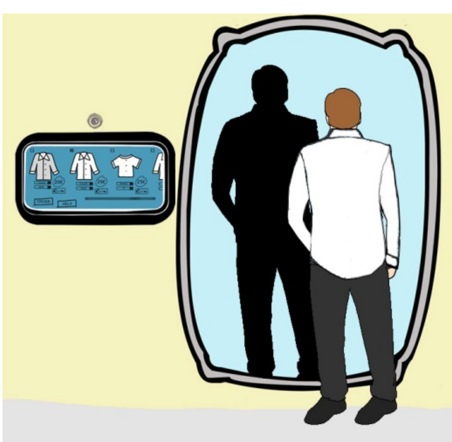
In the next pages you will find three brief texts each describing an individual trying to make a purchase decision with some technology-enabled assistance available in the shop. Each scenario will be followed by the same set of questions. **Please read through the scenarios carefully and imagine yourself in it.** When you are ready, please click "next" to continue.

Scenario1 (male)

SMART MIRROR

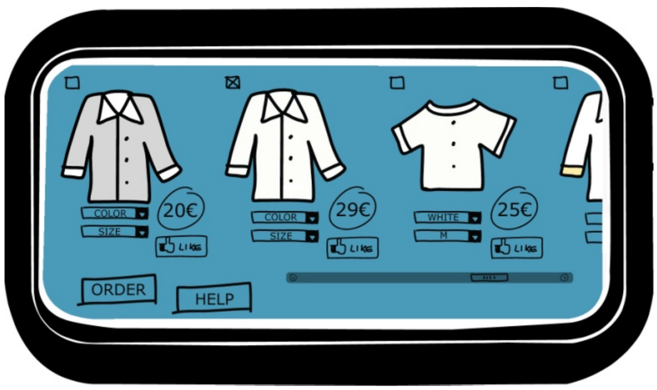
Tom enters the floor dedicated to men’s clothing in a large department store. He needs an outfit for his upcoming job interview. Therefore he is looking for a white shirt and a pair of dark trousers. The floor is huge and full of different brands with different styles. He looks for a shop assistant to get some advice concerning where to find the business outfits, but all shop assistants seem to be busy at the moment. So he picks two shirts and a pair of trousers and takes them into the fitting room. The trousers fit very well, but none of the shirts suit his taste.

He uses the Smart Mirror in the cabin for inspiration on shirts that could fit well to the trousers and are available in the store: Pressing a button, Tom activates the Smart Mirror function; the Smart Mirror scans Tom’s body.



Now Tom interacts with the Smart Mirror and it proposes a list of shirts which could fit well to the trousers on a small screen located next to the Smart Mirror, based on the occasion (formal outfit/interview outfit) and his age and size. He has the option to filter the given list based on different criteria (size, colour, brand, on sale etc).

He filters the options based on price (less than 30 Euro) and colour (white). Then, he browses the options and chooses five shirts to try on. He orders his favourite ones via touch screen and a shop attendant delivers them to him.

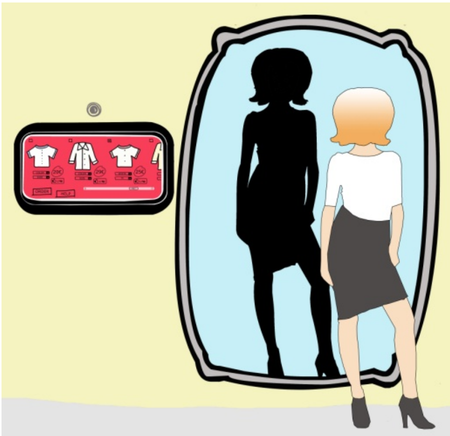


Scenario1 (female)

SMART MIRROR

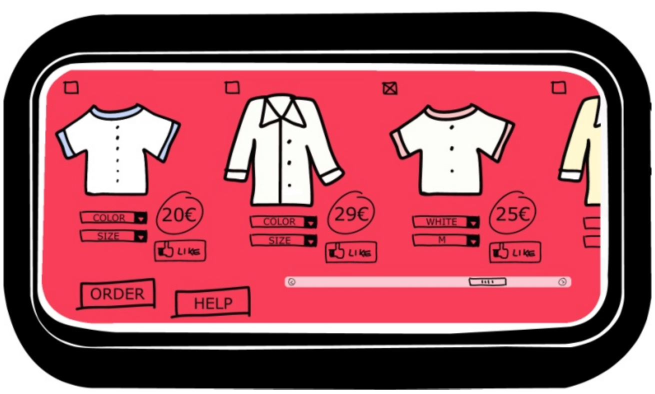
Lisa enters the floor dedicated for women clothing in a large department store. She needs an outfit for her upcoming job interview. Therefore she is looking for a white blouse and a dark skirt. The floor is huge and full of different brands with different styles. She looks for a shop assistant to get some advice concerning where to find the business outfits, but all shop assistants seem to be busy at the moment. So she picks two blouses and a skirt and takes them into the fitting room. The skirt fits very well, but none of the blouses suit her taste.

She uses the Smart Mirror in the cabin for inspiration on blouses that could fit well to the skirt and are available in the store: Pressing a button, Lisa activates the Smart Mirror function; the Smart Mirror scans Lisa's body.



Now Lisa interacts with the Smart Mirror and it proposes a list of blouses which could fit well to the skirt on a small screen located next to the Smart Mirror, based on the occasion (formal outfit/interview outfit) and her age and size. She has the option to filter the given list based on different criteria (size, colour, brand, on sale etc).

She filters the options based on price (less than 30 Euro) and colour (white). Then, she browses the options and chooses five blouses totry on. She orders her favourite ones via touch screen and a shop attendant delivers them to her.



Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewhat	Un-decided	Agree Some-what	Agree	Strongly Agree
I would like to shop in stores which have such							

technologies.							
I would use this technology frequently.							
I wish this technology was already available.							
I intend to use the presented technology if available.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
I think using the presented technology will help me find what I want faster and easier in the shop.							
The presented technology will make shopping more convenient for me.							
Overall, I think the presented technology will be useful for me.							
The presented technology will improve my shopping experience.							
The presented technology will fit my shopping needs.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
Learning how to use the presented technology seems easy for me.							
I think my interaction with this technology would be clear and understandable.							

The presented technology appears to be easy to use.							
It would be easy for me to become skilful at using the presented technology.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
My friends and/or family would be impressed to hear that I use this technology.							
My friends and/or family would be interested to use this technology.							
I think that using this technology would enhance my image.							
I think most people in my community will use the presented technology for shopping.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
The presented technology will make the shopping more fun for me.							
I will enjoy shopping more in shops with this technology.							
The presented technology will make the shopping very entertaining.							
The presented technology would feel like playing a game for me.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un- decided	Agree Some- what	Agree	Strongly Agree
I would prefer a retail store where the presented technology is available to use over an ordinary store.							

Scenario2 (male)

SMART MIRROR

After trying on the five shirts he has ordered via touch screen to the fitting room, Tom has three white shirts in his consideration set. He wants to buy just one. Furthermore, he has never bought from these brands, which is why he doesn't know about their quality.

Given that he is quite sensitive about the Price-Performance ratio (Preis-Leistungs-Verhältnis) of any product he buys, he interacts with the Smart Mirror again. While trying on each shirt, he touches the shirt on the Mirror and the details of the product as well as reviews on the products from other customers appear in an information box in the corner of the Mirror.

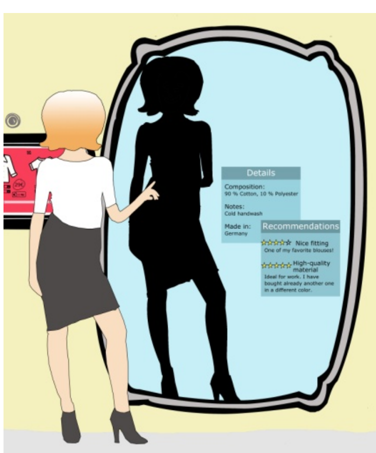
He chooses the one with the best review and buys the white shirt and the trousers. Being confident of his choices, he is looking forward to convince his new boss in the upcoming job interview.

Scenario2 (female)

SMART MIRROR

After trying on the five blouses she has ordered via touch screen to the fitting room, Lisa has three white blouses in her consideration set. She wants to buy just one. She has never bought from these brands and doesn't know the quality.

Given that she is quite sensitive about the Price-Performance ratio (Preis-Leistungs-Verhältnis) of any product she buys, she interacts with the Smart Mirror again. While trying on each blouse, she touches the blouse on the Mirror and the details of the product as well as reviews on the products from other customers appear in an information box in the corner of the Mirror.



She chooses the one with the best review and buys the skirt and the blouse. Being confident of her choices, she is looking forward to convince her new boss in the upcoming job interview.

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
I would use this technology frequently.							
I would like to shop in stores which have such technologies.							
I intend to use the presented technology if available.							
I wish this technology was already available.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
The presented technology will make shopping more convenient for me.							
I think using the presented technology will help me find what I want faster and easier in the shop.							
The presented technology will fit my shopping needs.							
The presented technology will improve my shopping experience.							
Overall, I think the presented technology will be useful for me.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree

I think my interaction with this technology would be clear and understandable.							
Learning how to use the presented technology seems easy for me.							
It would be easy for me to become skilful at using the presented technology.							
The presented technology appears to be easy to use.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
My friends and/or family would be interested to use this technology.							
My friends and/or family would be impressed to hear that I use this technology.							
I think most people in my community will use the presented technology for shopping							
I think that using this technology would enhance my image.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
I will enjoy shopping more in shops with this technology.							
The presented technology will make the shopping more fun for me.							
The presented technology would feel like playing a							

game for me.							
The presented technology will make the shopping very entertaining.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
I would prefer a retail store where the presented technology is available to use over an ordinary store.							

Scenario3 (male)

Mobile App

Paul and his friends are discussing the advantages of Tablets (Tablet Computers) and how practical they can be. One friend says that he could load all his materials on his Tablet to work on it while sitting in the train, the other is fascinated with the possibility to find additional information he might need through the internet and the other one uses his Tablet to write comments and notes directly in the documents while sitting in the train or during lectures and project presentations.

Being convinced of its advantages, Paul decides to purchase a Tablet. Few days later, he enters a very large electronics store and heads to the Tablet section. He goes through the assortment of Tablets in the store. Soon he finds a Tablet that suites his taste. The design is very nice and it has all the features he desires, but unfortunately it is too expensive.

He opens the store App in his Smartphone to find out if there is a similar (with the same main functions) but cheaper product. He scans the barcode of the Tablet he likes and it appears on his phone.

Then he chooses the category “Similar Products” and filters all the functions he would like his new Tablet to have.

Three different Tablets fit his requirements and show up on his screen.

He is able to directly compare all the features: price, brand, technical features (front camera, rear camera, expandable storage, etc) presented in an easy to compare matrix. By clicking on each option, he has the possibility to look for more detailed information of every Tablet in particular.

Paul always needs some time to think about a bigger spending. He saves the search options in his "Dream Box" to get to see them later.

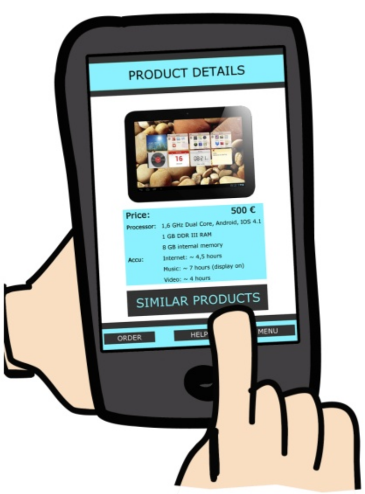
Scenario3 (female)

Mobile App

Julia and her friends are discussing the advantages of Tablets (Tablet Computers) and how practical they can be. One friend says that she could load all her materials on her Tablet to work on it while sitting in the train, the other is fascinated with the possibility to find additional information she might need through the internet and the other one uses her Tablet to write comments and notes directly in the documents while sitting in the train or during lectures and project presentations.

Being convinced of its advantages, Julia decides to purchase a Tablet. Few days later, she enters a very large electronics store and heads to the Tablet section. She goes through the assortment of Tablets in the store. Soon she finds a Tablet that suites her taste. The design is very nice and it has all the features she desires, but unfortunately it is too expensive.

She opens the store App in her Smartphone to find out if there is a similar (with the same main functions) but cheaper product. She scans the barcode of the Tablet she likes and it appears on her phone.



Then she chooses the category “Similar Products” and filters all the functions she would like her new Tablet to have.

Three different Tablets fit her requirements and show up on her screen.

She is able to directly compare all the features: price, brand, technical features (front camera, rear camera, expandable storage, etc) presented in an easy to compare matrix. By clicking on each option, she has the possibility to look for more detailed information of every Tablet in particular.

Julia always needs some time to think about a bigger spending. She saves the search options in her “Dream Box” to get to see them later.

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewhat	Un-decided	Agree Some-what	Agree	Strongly Agree
I wish this technology was already available.							
I intend to use the presented technology if available.							

I would use this technology frequently.							
I would like to shop in stores which have such technologies.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
Overall, I think the presented technology will be useful for me.							
The presented technology will improve my shopping experience.							
The presented technology will fit my shopping needs.							
The presented technology will make shopping more convenient for me.							
I think using the presented technology will help me find what I want faster and easier in the shop.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
The presented technology appears to be easy to use.							
It would be easy for me to become skilful at using the presented technology.							
I think my interaction with							

this technology would be clear and understandable.							
Learning how to use the presented technology seems easy for me.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
I think that using this technology would enhance my image.							
I think most people in my community will use the presented technology for shopping							
My friends and/or family would be interested to use this technology.							
My friends and/or family would be impressed to hear that I use this technology.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
The presented technology will make the shopping very entertaining.							
The presented technology would feel like playing a game for me.							
I will enjoy shopping more in shops with this technology.							

The presented technology will make the shopping more fun for me.							

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewhat	Un-decided	Agree Some-what	Agree	Strongly Agree
I would prefer a retail store where the presented technology is available to use over an ordinary store.							

Online Information Dependency

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewhat	Un-decided	Agree Some-what	Agree	Strongly Agree
When I require information, I need to use the internet.							
Internet is the preliminary (most important) source of information for me.							
Internet is the first source I check when I need a certain information							

Media Dependency Part I

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

<u>Internet helps you to…</u>

	Strongly disagree	Disagree	Disagree Somewhat	Un-decided	Agree Some-what	Agree	Strongly Agree
stay on top of what is happening in the community							
find out how the country is doing.							
keep up with world events.							
gain insight into why you do some of things that you do.							
imagine what you will be like as you grow older.							
observe how others cope with problems or situations like yours.							

Media Dependency Part II

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

<u>Internet helps you to…</u>

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
discover better ways to communicate with others.							
think about how to act with friends, relatives, or people you work with.							
get ideas about how to approach others in important or difficult situations							
give you something to do with your friends.							
have fun with your family or friends.							

be a part of events you enjoy without having to be there.							

Media Dependency Part III

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

<u>Internet helps you to…</u>

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
to stop thinking about work and problems after a hard day or week.							
relax when you are by yourself.							
have something to do when nobody else is around.							

Personal Innovativeness in IT

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly disagree to 7=strongly agree)

	Strongly disagree	Disagree	Disagree Somewh at	Un-decided	Agree Some-what	Agree	Strongly Agree
I like to experience products that use new technologies.							
Among my friends, I am usually the first to explore new information technologies.							
I feel comfortable using new information technologies							
In general, I am hesitant to try out new information technologies.							

Questions for Internet Usage

Following we would like to speak about your internet use behavior. With “Internet”, we mean any activity which you do in the internet including communications, searching, entertainment, education etc. and with any internet-enabled device that you own (e.g. desktop, laptop, tablet, and smart phone,etc).

The following questions are exclusively about your personal Internet use habits.

On average, how frequently do you use Internet?

Choose one of the following answers

( ) Never/almost never

( ) Less than once a month

( ) A few times a month

( ) A few times a week

( ) About once a day

( ) Several times a day

On average, how much time do you spend daily on the Internet?

Choose one of the following answers

( ) less than half an hour

( ) from half an hour to an hour

( ) 1-2 hours

( ) 2-3 hours

( ) more than 3 hours

Internet affinity

Please indicate the extent to which you agree or disagree with the following statements: (scale 1=strongly agree to 7=strongly disagree)

	Not at all	To a very small extent	To a small extent	To a mode-rate extent	To a fairly great extent	To a great extent	To a very great extent
Connecting to Internet is one of my main daily activities.							
If the Internet is down I really miss it.							
Internet is important in my life.							
It doesn't bother me to be without internet for several days							
I would feel lost without internet							

Questions for Internet Usage 2

Please indicate the extent to which you use Internet to perform the following tasks:

	Not at all	To a very small extent	To a small extent	To a mode-rate extent	To a fairly great extent	To a great extent	To a very great extent
Communication with others (not including email)							
Education							
Entertainment							
Gathering information (e.g. for personal needs, product information)							
Work/Business							

Purchasing/Shopping							

Shopping behavior

How frequently do you use each of the following channels during the below-mentioned purchase steps?

Finding out about new products

	Never	Rarely < 10 % chances	Occa-sionally 10 % - 30 % chances	Some-times 30 % - 50% chances	Fre-quently 50 % - 70% chances	Usually 70 % - 90% chances	Every time
Internet from home							
Mobile Internet							
Physical store							

Searching for information on specific products

	Never	Rarely < 10 % chances	Occa-sionally 10 % - 30 % chances	Some-times 30 % - 50% chances	Fre-quently 50 % - 70% chances	Usually 70 % - 90% chances	Every time
Internet from home							
Mobile Internet							
Physical store							

Comparing and evaluating alternatives

	Never	Rarely < 10 % chances	Occa-sionally 10 % - 30 % chances	Some-times 30 % - 50% chances	Fre-quently 50 % - 70% chances	Usually 70 % - 90% chances	Every time

Internet from home							
Mobile Internet							
Physical store							

Purchasing and paying for products

	Never	Rarely < 10 % chances	Occa-sionally 10 % - 30 % chances	Some-times 30 % - 50% chances	Fre-quently 50 % - 70% chances	Usually 70 % - 90% chances	Every time
Internet from home							
Mobile Internet							
Physical store							

Device ownership

Which of the following computer devices do you own?

( ) Desktop computer

( ) Laptop

( ) Tablet PC

( ) Smart Phone

Which of your devices you use **most** to access internet?

( ) Desktop computer

( ) Laptop

( ) Tablet PC

( ) Smart Phone

( ) None

General Questions II

Which of the following best describes your highest education level?

( ) 8th grade or less

( ) Some high school (Grade 9-11)

( ) Graduated from high school

( ) 1-3 years of college/university

( ) Graduated from college, graduate or postgraduate school

( ) Refused to answer

What is/was your university major? (Feel free to answer in German)

___

What best describes your employment status? (Select all that apply)

( ) Full-time job

( ) Part-time job / by the hour / occasionally

( ) Unemployed

( ) Retired

( ) House wife / House husband

( ) Full-time student

( ) Part-time student

( ) Refused to answer

How much is your disposable income (Haushaltsnettoeinkommen)

( )		**Less than**	**500**	**EUR**
( )	500	to	999	EUR
( )	1.000	to	1.499	EUR
( )	1.500	to	1.999	EUR
( )	2.000	to	2.499	EUR
( )	2.500	to	2.999	EUR
( )	3.000	to	3.499	EUR
( )	3.500	to	3.999	EUR
( )	4.000	to	4.499	EUR
( )	4.500	to	4.999	EUR
( )	5.000	to	5.500	EUR
( )		More than	5.500	EUR
( )	Refused to answer			

What is your nationality?

We sincerely thank you and appreciate your time, dedication, and participation in our online survey. As a thank you for sharing your time, we would like to invite you to enter your email address and be part of our prize drawing.

____

Thank you for taking time out to participate in our survey. We truly value the information you have provided.

If you have any questions about the survey, please contact us at sara.kheiravar@tuhh.de or call 040428784522.

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