Computers in Human Behavior 26 (2010) 697–704

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

In-store consumer behavior: How mobile recommendation agents influence usage intentions, product purchases, and store preferences

Tobias Kowatsch [a,*], Wolfgang Maass [a,b]

[a] Institute of Technology Management, University of St. Gallen, Dufourstrasse 40a, 9000 St. Gallen, Switzerland
[b] Research Center for Intelligent Media, Hochschule Furtwangen University, Robert-Gerwig-Platz 1, 78120 Furtwangen, Germany

ARTICLE INFO

Article history:
Available online 4 February 2010

Keywords:
Consumer behavior
Decision support system
Personal digital assistant

ABSTRACT

Product information given in purchase situations influences purchase behavior. In online purchase situations, the use of recommendation agents increases the value of product information as information becomes adaptive and thus more relevant to consumers' information needs. Correspondingly, mobile recommendation agents (MRAs) may also increase the value of product information in bricks-and-mortar stores. In this sense, product information is not only adaptive but can also be requested at any place such as in front of products consumers are interested in. Because unprecedented, we investigate the use of a MRA that is virtually bound to a physical product via an RFID-enabled mobile device and provides product information. Based on Theory of Planned Behavior, Innovation Diffusion Theory, and Technology Acceptance Model, we develop a model to better understand the impact of MRAs on usage intentions, product purchases and store preferences of consumers. This model is then tested in a lab experiment ($n = 47$). Among high usability scores, results indicate that perceived usefulness of a MRA influences product purchases, predicts usage intentions and store preferences of consumers. Thus, new business models for retail stores can be considered in which MRAs satisfy both the information needs of consumers and the communication needs of retailers.

© 2010 Elsevier Ltd. All rights reserved.

1. Introduction

Consumers depend on precise and comprehensible product information at the point of sale. For example, consumers with food allergies need to know about the ingredients of groceries and consumers that buy a memory card for a digital camera need to know if both products are compatible with each other. Product information therefore strongly influences purchase behavior as found by consumer research for in-store shopping situations (Tellis & Gaeth, 1990). In the case of online purchase situations, the value of product information can be increased further with the use of recommendation agents (RA) as they "elicit the interests or preferences of individual users for products either explicitly or implicitly, and make recommendations accordingly" (Bo & Benbasat, 2007, p. 137). In this sense, product information provided by online RAs becomes adaptive and therefore more relevant to individual consumers' information needs, whereas product information on printed product labels is static by definition. Correspondingly, several studies revealed that online RAs help to reduce search complexity and consumers' information overload (Häubl & Trifts, 2000; Todd & Benbasat, 1999), improve decision quality (Pereira, 2001), increase trust in decisions (Gregor & Benbasat, 1999), and finally, influence consumer behavior and purchase intentions (Bo & Benbasat, 2007; Häubl & Trifts, 2000; Kamis, Koufaris, & Stern, 2008). In practice, they are restricted to online applications and are adopted by providers of product information, e.g., for car configurations, such as offered by Toyota (carconfig.toyota-europe.com), collaborative product recommendations (e.g., Amazon.com) or recommendations of recipes based on particular ingredients a consumer has available (e.g., allrecipes.com).

As RAs are used through websites at home, they may also be used on mobile devices in in-store purchase situations for product information acquisition. Correspondingly, mobile applications are currently being developed for consumers to communicate with physical products (Maass & Varshney, 2008). Thus, mobile shopping assistants such as Impulse (Youll, Morris, Krikorian, & Maes, 2000), MyGrocer (Kourouthanassis & Roussos, 2003), MASSI (Metro AG), the Tip'n Tell client (Maass & Filler, 2006), the Mobile Prosumer (Resatsch, Sandner, Leimeister, & Krcmar, 2008), EasiShop (Keegan, O'Hare, & O'Grady, 2008), or APriori (von Reischach, Guinard, Michahelles, & Fleisch, 2009) allow to request product information directly at the point of sale. For example, a garment is identified by a mobile barcode or RFID reader device and then provides its information such as the recommended sales price, its producer or other products that fit with it. In that case, physical products can be enriched with new digital product information services relevant to the consumer. This would not only change the way retail stores are

* Corresponding author. Tel.: +41 71 224 7244; fax: +41 71 224 7301.
E-mail address: tobias.kowatsch@unisg.ch (T. Kowatsch).

0747-5632/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.chb.2010.01.006

perceived by consumers, e.g., they might request product information directly at the point of sale instead at home, but it would also have managerial implications for retailers and providers of product information. In particular, the use and impact of mobile recommendation agents (MRAs) in in-store shopping situations are a main concern from both consumer's and retailers' perspective.

Up until now, little research has been conducted on the utility of RAs for in-store purchase decision-making. For example, Westerman, Tuck, Booth, and Khakzar (2007) found that a desktop-based RA improves the quality of purchase decisions by providing recommendations based on a weighted adding model. In another lab experiment, product information provided by a MRA was perceived as being better than static product information (e.g., information printed on product labels) particularly for product bundle purchases in in-store situations (Kowatsch, Maass, Filler, & Janzen, 2008; Maass & Kowatsch, 2008a). Further, the existence of personalized cues provided by MRAs and indicating the attractiveness of a product improves the quality of product consideration sets (van der Heijden, 2006). But it is still open, (1) whether MRAs are adopted for product information acquisition in retail stores, (2) by which factors they are adopted, (3) if they influence purchase behavior, and finally, (4) whether MRAs influence the consumers' preferences in selecting retail stores that provide access to them.

This paper provides answers to these questions by conducting a lab experiment. It is organized as follows. Next, we will discuss related literature on product information and RAs before we develop our research model that is based on Theory of Planned Behavior (Ajzen, 1991), Innovation Diffusion Theory (Rogers, 2003), and Technology Acceptance Model (Davis, 1989). Then, the model is tested empirically as described in the methodology section. The results and limitations of the study are discussed subsequently before we conclude this paper by a summary and an outlook on future work.

2. Related work

Online and mobile E-Commerce applications are specializations of economic markets and span a continuum of institutionalized environments, in which customer-oriented transactions on products and services are performed (Bakos, 1998). In E-Commerce applications, physical products are represented by digital product descriptions, whereas in-store shopping situations support users with direct perceptions of products by touch, smell, and other sensual cues (Citrin, Stem, Spangenberg, & Clark, 2003; McCabe & Nowlis, 2003). Recently, several studies evaluated the impact of digital replications with different sensual experiences by virtual reality simulations, which facilitate further transfer of physical shopping experiences into digital shopping environments (Lee & Chung, 2008; Zhenhui & Benbasat, 2004). By contrast and consistent with our approach, the opposite direction investigates how E-Commerce services can be embedded into physical shopping environments by desktop-based (Westerman et al., 2007) or mobile and ubiquitous computing technologies (Junglas & Watson, 2006; Kleijnen, de Ruyter, & Wetzels, 2007; van der Heijden, 2006; Watson, Pitt, Berthon, & Zinkhan, 2002). In these scenarios, rich product information becomes available at the point of sale and can be dynamically adapted to consumers' needs by using a product interface that embeds value added services. In the current work, we focus on a particular service in the form of a recommendation agent (RA) that provides product information. As the relevance of RAs for purchase situations was discussed in the introduction, we describe their interrelation with product information subsequently.

Purchase decisions depend on product information that can be imperfect for a number of reasons, "such as the proliferation of competing brands, the difficulties of exhaustive search or sampling, biases in product evaluation, constant product innovation or consumer mobility" (Stahl & Freudenschuss, 2006, p. 1932). This information asymmetry between producers and consumers results in emphasizing price and quality attributes during purchase decisions at the point of sale (Tellis & Gaeth, 1990). If a customer knows little about the product's quality, he will optimize his or her choice according to price considerations. With increased product information about expected quality, consumers tend towards rational decisions on the expected utility over both attributes (Tellis & Gaeth, 1990). Correspondingly, by using a mobile recommendation agent (MRA), product information asymmetry between producers and consumers can be reduced in front of the product shelf. For instance, product reviews provided by professional magazines or user-communities via the MRA may reveal information on the quality of a product, thus may change the purchase behavior (von Reischach et al., 2009).

Furthermore, influence on shopping experience is distinguished into emotional impressions that affect customers' moods and product information that affects rational decision-making (Groeppel & Bloch, 1990). Consistent with the current work, MRAs are intrinsically focused on product information (van der Heijden, 2006). In addition, product information can be classified into singular product information or relational product information. Singular product information describes a particular product (i.e., product features). By contrast, relational product information describes product sets that can be classified into product complementary sets (e.g., product bundles) and product similarity sets (alternative products). Several techniques have been used for the automatic derivation of product similarity sets (Kurkovsky & Harihar, 2006). Product similarity sets are further classified whether they are solely derived from product features such as content-based recommendations (Maidel, Shoval, Shapira, & Taieb-Maimon, 2008) or indirectly derived via preferences and decisions of other users such as social or collaborative recommendations (Esslimani, Brun, & Bayer, 2008; Yang, Li, & Zhang, 2009; Zhang & Li, 2008). In the current work, both singular and relational product information is covered but only product similarity sets based on product features are provided to the consumer through the MRA.

Finally, we investigate a conversational MRA that uses a question-and-answer-based dialog system (Gurevych & Mühlhäuser, 2007; Maass & Janzen, 2007). In this sense, product information is requested by asking questions, e.g., *What is the price of this product?* (singular product information) or *Are there accessories available?* (relational product information).

3. Research model

In the following, we develop our research model that investigates the use of a mobile recommendation agent (MRA) for product information acquisition in in-store purchase situations. The MRA is implemented on an RFID-enabled mobile device that allows the identification of products and therefore extends traditional product information capabilities on printed product labels by providing relevant product information on demand. We study the adoption of the MRA by applying Innovation Diffusion Theory (IDT) (Rogers, 2003), Technology Acceptance Model (TAM) (Davis, 1989), and Theory of Planned Behavior (TPB) (Ajzen, 1991).

According to IDT, the MRA represents an innovation that a consumer can adopt for product information acquisition in purchase situations. Another research stream applies intention-based models to understand the adoption of IT. Accordingly, corresponding models such as TPB are grounded in social psychology to identify attitudes, social influences and facilitating conditions that predict the behavioral intention of usage. The behavioral intention to use a MRA for product information acquisition predicts its adoption, respectively. For instance, TAM is based upon this line of research.

Two constructs from prior research are adequate to be utilized in our model. The first is perceived usefulness, which is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). In our context, perceived usefulness refers to the degree to which a customer believes that using a MRA would enhance his or her performance to acquire relevant information for product purchases. Regarding TPB, perceived usefulness as believe towards a future behavior predicts the intention to use a MRA for product information acquisition. Thus, we hypothesize the following relationship:

H1. Perceived usefulness of a MRA has a positive relation with the intention to use that MRA for product information acquisition.

In our context, a MRA can only be used with products that can be identified, e.g., through barcode or radio frequency identification. Therefore, customers are likely to select only those retail stores that enable them to use the MRA. We call them MRA-enabled retail stores. According to Bitner (1992, p. 67), we assume MRA-enabled retail stores to be more in the role of a facilitator that supports the ability of customers to carry out their respective activities, i.e., to use a MRA for product information acquisition. Thus, store preference reflects rather a positive inclination towards a store than a primary preference factor of a customer in our research. In line with TPB, the behavioral intention to prefer MRA-enabled retail stores is predicted by the usefulness of the MRA as perceived by consumers. In addition, Kamis et al. (2008) found that perceived usefulness of an RA-enabled online store strongly predicts the intention to return to it. This is also related to our research as return reflects store preference. We postulate therefore the following relationship:

H2. Perceived usefulness of a MRA has a positive relation with the intention to prefer MRA-enabled retail stores for product information acquisition.

Next, the MRA supports consumers in buying situations as it helps them to find relevant product information. With higher degrees of perceived usefulness of the MRA's dialog system, buying intentions are increased as relevant information for purchase decisions is provided. This relation is also supported by marketing and information system research (Kamis et al., 2008; Tellis & Gaeth, 1990), thus we hypothesize:

H3. Perceived usefulness of the MRA has a positive relation with the intention to purchase a product after using it for product information acquisition.

The second TAM construct used in our model as predictor variable is perceived ease of use, which refers to the degree "to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). Here, the MRA supports the consumer to acquire product information in in-store purchase situations. Consistent with TPB, TAM and recent work (Hasan & Ahmed, 2007; Maass & Kowatsch, 2008a), we hypothesize the following relationship:

H4. Perceived ease of use of the MRA has a positive relation with the intention to use it for product information acquisition.

And finally, in line with Davis (1989), Hasan and Ahmed (2007), and Kamis et al. (2008), perceived ease of use predicts perceived usefulness for desktop applications, human computer interfaces and online recommendation systems. Additionally, it was found that ease of use predicts relative advantage of dynamic product information provided by MRAs (Maass & Kowatsch, 2008a). Here, relative advantage is similar to the usefulness construct as discussed by Moore and Benbasat (1991). Hence, perceived ease of use of the MRA is suggested to influence its perceived usefulness as well:

H5. Perceived ease of use of a MRA has a positive relation with perceived usefulness of that MRA for product information acquisition.

To summarize, Fig. 1 illustrates our research model.

4. Method

In order to test the research model, we first developed a mobile recommendation agent (MRA) before we conducted a lab experiment. In the following, the implementation of the MRA is described. Then, a detailed overview of the lab experiment is presented.

4.1. Mobile recommendation agent

In contrast to the barcode-based MRA of van der Heijden (2006), our MRA is implemented on an RFID-enabled PDA (HP iPAQ Pocket PC with an Socket 6E RFID reader) by using the .Net Compact Framework. It uses a dialog web service and a linguistic knowledge base. Both components are part of the Tip 'n Tell middleware for smart products (Maass & Filler, 2006), which are implemented by a web service architecture on the basis of the Jena 2.0 system (jena.sourceforge.net) that allows the integration of reasoning mechanisms, such as Fact++. Reasoning is used to process questions directed at products by users of the MRA. Correspondingly, the graphical user interface of the MRA decodes user questions into requests, which are sent to the dialog web service. The PDA is connected to the Tip 'n Tell middleware via wireless LAN technologies.

In our implementation, users are in the role of consumers in in-store shopping situations and initiate a dialog with a product by identifying them with the RFID reader attached to the PDA. Therefore, products need to be annotated with RFID-tags (ISO15693, HF range with 13.56 MHz), which carry URL references to the location where their product information is stored. With the help of rules and reasoning mechanisms of the Tip 'n Tell middleware, not only information of a particular product such as its price or description can be requested but also information that allows to ask for the compatibility or complementary of two different products (e.g., for the recommendation of product bundles).

4.2. Lab experiment

A lab experiment was conducted to test the usability of the MRA and to evaluate our research model. The sampling procedure was as follows. We e-mailed an invitation to all bachelor students studying media and computer science at our University. In this

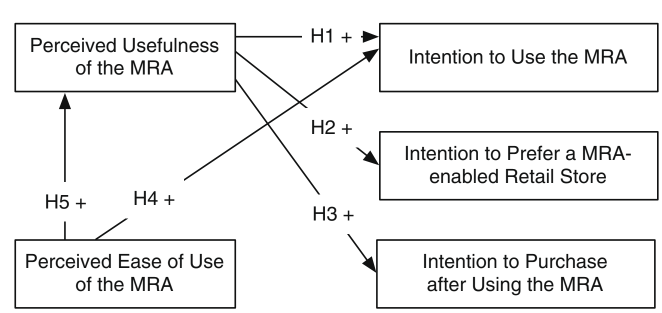

Fig. 1. Research model. *Note:* MRA stands for mobile recommendation agent.

invitation, the experiment was promoted by claiming that each participant will receive 8 Dollars. Further, it contained a link to a website, on which the students were able to register for the experiment by choosing one out of 50 time slots – each slot intended for one student. After all slots were booked out, no one could register anymore. Therefore, only the first 50 subjects were allowed to participate and to receive the 8 Dollars after the experiment.

A pre-test with several bachelor students was carried out to get preliminary feedback in advance of the experiment, which was then used to optimize the MRA and the instructions of the questionnaire. The MRA was developed for consumers to acquire relevant product information in retail stores. This is accomplished in two consecutive tasks. First, the user starts the dialog with the MRA by a touching gesture at a product by which the product's ID is read via the RFID reader of the PDA as shown in Fig. 2. Second, the user asks for product information by using the question-and-answer-based dialog function of the MRA, which can be seen in Fig. 3. In order to test the usability of the MRA, both tasks had to be considered. For this purpose, we evaluated the usability of both the touching gesture and the dialog function with the system usability scale (SUS) which was developed by Brooke (1996). The usability test was required to indicate the maturity of our MRA implementation based upon the research model is evaluated. In this sense, over-average usability scores are required to discuss profound implications of the results.

In the first part of the experiment, the subjects were told that they are customers of a retail store that sells mobile navigation units and accessories as shown in Fig. 2. Seven mobile navigation units were equipped with an RFID-tag that was fixed below a tally labeled *touch me*. The tally was used to inform the subjects on which spot of the product they could start the MRA's dialog function by the touching gesture. Subjects were instructed to buy one of the available mobile navigation units and one accessory. Product information could only be obtained by using the MRA as no paper-

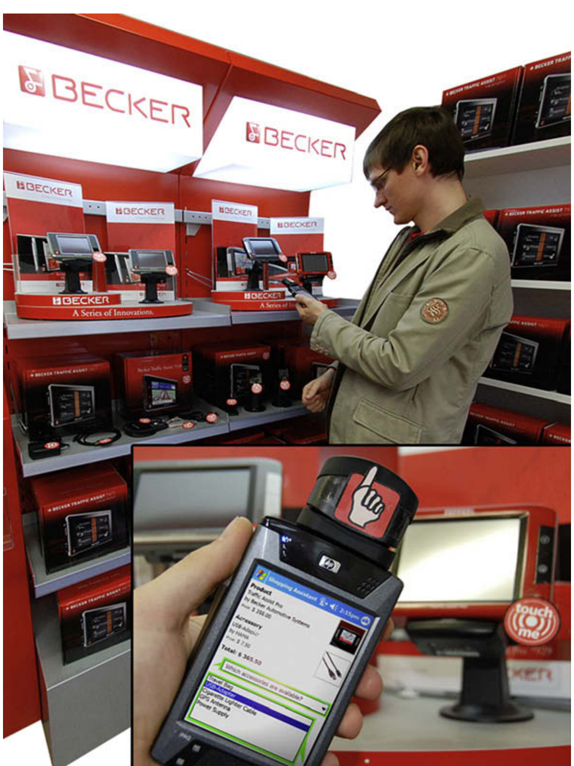

Fig. 2. The consumer starts the dialog function of the mobile recommendation agent with a touching gesture on the RFID-tagged product.

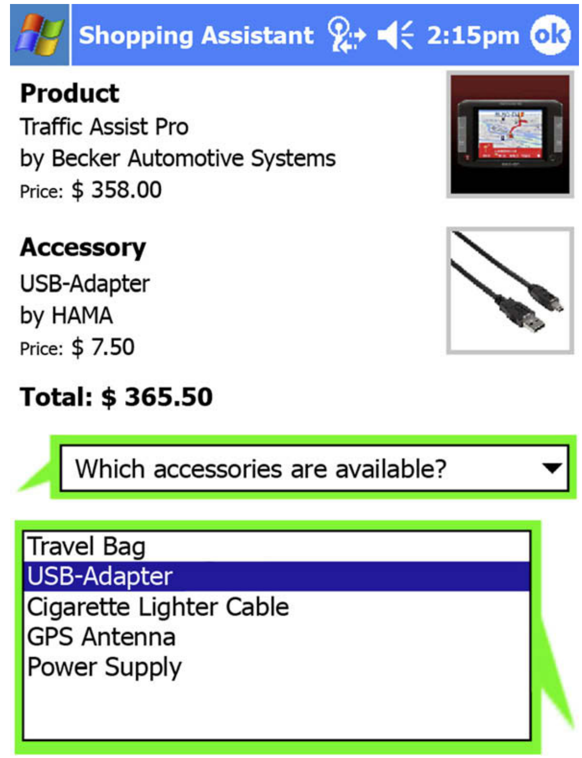

Fig. 3. Screenshot of the interface of the mobile recommendation agent. Here, the consumer asks for compatible accessories with the help of the dialog function.

based product labels were shown. This MRA-only treatment implies a possible future retail scenario that is supported by recent empirical findings of a similar lab experiment, in which product information provided by a MRA was perceived as being better than paper-based product information (Kowatsch et al., 2008; Maass & Kowatsch, 2008a). In that experiment, the implementation of the MRA is highly comparable with the MRA of our work as the implementation differs only in the way the questions towards a product are selected to acquire the corresponding product information, i.e., a pull-down menu with several questions rather than two buttons that represent two questions.

The subjects had to consider the following instructions for the purchase task: the mobile navigation unit had to be low-priced, had to support the USB-standard and had to include a 1 GB SD-Card. In addition, the accessory had to be compatible with the mobile navigation unit they chose. These constraints were formulated such that subjects had to ask several questions, thus getting trained with both touching gesture and dialog function. Name, producer, price and a small image of the product were shown immediately at the top of the screen after the pointing gesture was finished as can be seen in Fig. 3. The following four questions were available by the MRA's drop down list:

(a) Are there product details available? (e.g., 1 GB SD-Card, etc.).
(b) Which standards are supported? (e.g., USB, SD-Card).
(c) Which accessories are available? (e.g., USB-Adapter or bags that are compatible to the product in question).
(d) Are there alternative products? (e.g., other mobile naviga tion units).

Subjects had 10 min to finish this part of the experiment. Then, in the second part, subjects were given a questionnaire with the SUS items (Brooke, 1996). The questionnaire was also used to ask for the constructs of our research model. Items regarding the perceived characteristics usefulness and ease of use were adapted from existing scales (Kamis et al., 2008). Furthermore, three items were used to measure the behavioral intention to use the MRA (Davis, 1989), product purchase intention and the intention to prefer a retail store that allows the usage of such kind of MRA (Kamis et al., 2008). According to Ajzen and Fishbein (1980), all three statements cover the three behavioral elements action (usage/purchase/prefer), target (MRA) and context (product information/product/retail store) as can be seen in Table 2. All items were based on seven-point Likert scales, ranging from extremely disagree (1) to extremely agree (7). At last, the questionnaire was used to collect demographic data and to ask for the length of the experiment and the comprehensibility of the instructions.

5. Results

Thirty-eight male and nine female students participated in the lab experiment. Their age ranged from 20 to 24 ($n = 31$) and from 25 to 29 ($n = 16$). The instructions of the experiment and the questionnaire were perceived as being reasonable (*Mean* = 6.64; *SD* = .53) and acceptable on its length (*Mean* = 6.49; *SD* = .98). Reliability of the SUS items was tested with Cronbach's alpha, which resulted in viable .69 and .83 for the pointing gesture and the dialog function. Because the sample is obviously biased by gender, we evaluated whether the results are influenced by this variable. Accordingly, we conducted an analysis of variance for all theoretical constructs with gender being the independent variable. As a result, we found no significant differences for all constructs, i.e., the level of significance was above .05: SUS score for pointing gesture ($p = .80$), SUS score for dialog function ($p = .47$), perceived usefulness ($p = .28$), perceived ease of use ($p = .47$), intention to use ($p = .80$), intention to prefer ($p = .66$) and intention to purchase ($p = .14$). Therefore, gender did not influence the following results significantly.

In general, the SUS score ranges from 0 to 100 with 100 representing the best usability value (Brooke, 1996). Our SUS score of the pointing gesture was 78.8 on average and below the dialog function's score that yielded remarkable 85.8. This result can be explained by the free-text feedback of the subjects that predominantly addressed the slow speed of starting the dialog function with the touching gesture. This issue is based upon technical restrictions regarding the RFID reader's capabilities. In addition, some subjects requested the ability of the dialog system not only to ask for product information of one product but also to compare different products by their properties. This feature will be considered in the next stage of the MRA's development. Nevertheless, both SUS scores were highly significant above the neutral test value of 50 by applying *t*-tests for one sample. As a result, the overall usability of the MRA is promising with regard to its early development stage. Thus, the following test of the research model is based upon a usable MRA implementation. A summary of the descriptive statistics and the results of the usability test are shown in Table 1.

Consistent with prior research (Kamis et al., 2008; Komiak & Benbasat, 2006), partial least squares (PLS) was used for the data analysis of our research model. PLS belonging to structural equation modeling (SEM) was chosen over regression analysis, because SEM can analyze all of the paths in one analysis (Barclay, Thompson, & Higgins, 1995; Gefen, Straub, & Boudreau, 2000). PLS allows analyzing (1) the structural model for assessing the relationships among our theoretical constructs and (2) the measurement model for assessing the validity and reliability of our questionnaire items. In our research, all theoretical constructs were modeled as reflective, because their questionnaire items are manifestations of them (Barclay et al., 1995) and are expected to correlate with each other (Chin, 1998). By using G*Power3 (Faul, Erdfelder, Lang, & Buchner, 2007), a sample size of 31 was calculated for two predictors (Method: *F*-test, Multiple Regression – Omnibus) which would be good enough to detect PLS path coefficients with large effect sizes ($f^2 = .35$). A statistical power of .80 was used, which is common in

Table 1
Results of the system usability scale (SUS) (see Brooke, 1996) and one sample *t*-tests for both tasks and 47 subjects. *Note:* the average test value of 50 was used for the *t*-tests as the SUS score ranges between zero and 100.

	Starting the dialog by a touching gesture (Task 1)	Usage of the dialog to obtain product information (Task 2)
Number of Items	10	10
Cronbach's alpha	.69	.83
SUS score	78.8	85.8
Standard deviation	12.6	12.1
t-Value	16.3	19.6
p-Value	<.001	<.001

Table 2
Survey instrument and descriptive statistics ($n = 47$). *Note:* SFL (standardized factor loadings), *SD* (standard deviation).

	Construct and items	SFL
	Perceived usefulness of the MRA *Cronbach's alpha: .861 Mean: 5.73, SD: .81*	
PU1	Using this MRA can improve my performance to acquire product information	.720
PU2	Using this MRA can improve my productivity to acquire product information	.887
PU3	Using this MRA can improve my effectiveness to acquire product information	.897
PU4	I find using this MRA useful to acquire product information	.847
	Perceived ease of use of the MRA *Cronbach's alpha: .716 Mean: 6.27, SD: .81*	
PEU1	Learning to use the MRA to acquire product information would be easy for me	.713
PEU2	My interaction with the MRA is clear and understandable to acquire product information	.832
PEU3	It would be easy for me to become skilful at using the MRA to acquire product information	.515
PEU4	I find the MRA easy to use to acquire product information	.858
	Intention to use the MRA *Mean: 5.77, SD: 1.29*	
IU	I would use the MRA to acquire product information in retail stores	N/A
	Intention to purchase after using the MRA *Mean: 4.72, SD: 1.61*	
IP	I would purchase a product after I was using the MRA for product information acquisition	N/A
	Intention to prefer a MRA-enabled retail store *Mean: 4.23, SD: 1.59*	
IPS	I would prefer a retail store that allows me to use the MRA to acquire product information	N/A

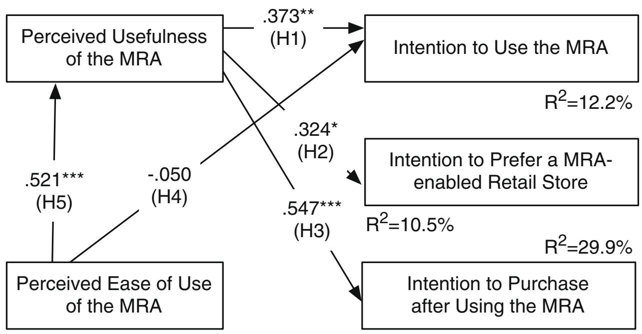

Fig. 4. Results of PLS analysis. *Note:* $^{*}p > .05$, $^{**}p < .01$, $^{***}p < .001$.

MIS research (Baroudi & Orlikowski, 1989; Cohen, 1977). Thus, the sample size of 47 subjects was sufficient for the lab experiment.

In order to test the validity of our constructs, we performed a confirmatory factor analysis using SEM with SmartPLS 2.0 and the bootstrapping resample procedure (Ringle, Wende, & Will, 2005). Although one item (PEU3) from the perceived ease of use scale had a factor loading below the recommended value of .70, we retained it in order to maintain continuity with prior research using the same scales. All of the items loaded significantly on their assigned latent variables. Thus, our scales show good convergent validity. The Cronbach's alpha values for all constructs are above the recommended .70 value, indicating good reliability (Nunnally, 1967). The factor loadings, Cronbach's alpha values, and descriptive statistics of all constructs are shown in Table 2.

The results of the PLS analysis can be seen in Fig. 4. First, the coefficient between perceived usefulness and the intention to use the MRA for product information acquisition is positive and significant ($\beta = .373$, $p < .01$). Second, the coefficients between perceived usefulness and the intention to prefer a retail store that allows the usage of the MRA for product information acquisition ($\beta = .324$, $p < .05$) and the intention to purchase a product after using the MRA ($\beta = .547$, $p < .001$) are both positive and significant. This supports H1, H2 and H3. In addition, the coefficient between perceived ease of use and perceived usefulness is positive and significant ($\beta = .521$, $p < .001$) supporting H5. By contrast, perceived ease of use does not significantly predict the intention to use the MRA for product information acquisition ($\beta = -.050$, $p > .05$). Therefore, H4 is not supported by our empirical data and possible explanations for this non-significant relationship are provided in the following section.

6. Discussion

6.1. Theoretical implications

Our study provides evidence for the usability of one particular mobile recommendation agent (MRA) for product information acquisition in in-store purchase situations. This result is valid for both tasks relevant for consumer-product communication. First, consumers start the dialog with the product by pointing at it with an RFID-enabled PDA on which the MRA is implemented. Participants may be already familiar with the semantics of this gesture representing *I mean you* or *I need something from you* or *I am interested in you* when they want to call someone's attention. Second, consumers use the question-and-answer-based dialog system of the MRA to request product information relevant to them. This dialog-based interaction has similarities with the communication of consumers and sales personnel (Maass & Kowatsch, 2008b). Thus, consumers are able to reuse knowledge learned from prior purchase situations, which may increase the MRA's usability. Although successfully tested for one particular instance of a MRA, the proposed communication design can therefore be reused and tested in other situations within a product's life cycle. For example, purchase transactions or product support activities can be started by touching gestures and supported by a dialog-based MRA.

Beside the over-average usability scores of the MRA, we found that the behavioral intention to use the MRA is strongly predicted by its perceived usefulness, which extends findings of prior research on the adoption of Information Systems (Davis, 1989; Kamis et al., 2008; Venkatesh, Morris, Davis, & Davis, 2003) for MRAs in in-store shopping situations. This indicates also, that the MRA is perceived as being useful and thus will be adopted by at least some of the subjects. Moreover, perceived usefulness of the MRA strongly predicts the intention to prefer a retail store that allows consumers to use it. And second, perceived usefulness also predicts the intention to buy a product after using the MRA. Both findings not only extend the work of Kamis et al. (2008) to in-store shopping situations, but are also relevant to store managers as discussed in the next section.

In contrast to the findings of Davis (1989), perceived ease of use does not significantly predict usage intentions of our MRA. Beside the sample size only indicating big effects in the PLS path model, other predictors from IDT such as compatibility or complexity (Moore & Benbasat, 1991; Rogers, 2003) or other constructs such as trust (Komiak et al., 2006), risk and convenience (Ponder, Lueg, & Williams, 2006) or self-consciousness when using MRAs in public areas (Serif & Ghinea, 2008) might be more relevant and therefore should be investigated further. Moreover, the interface design of MRAs has been of little importance in our research yet, which might be another reason for this non-significant relationship. In this sense, MRAs are primarily problem-solving intermediaries that are valued by their contribution of solutions to a problem and thus, perceived usefulness is much more important than ease of use. However, ease of use enables the adoption of MRAs as it strongly predicts the usefulness of MRAs, which supports prior research (Davis, 1989; Kamis et al., 2008).

6.2. Practical implications

As a result of the empirical findings, the use of MRAs and corresponding infrastructures might increase the sales volume of retail stores through an increase of consumer frequency – predicted by consumers' intention to prefer MRA-enabled retail stores – and the potential of product purchases – predicted by the consumers' intention to purchase a product after using the MRA. Therefore, we recommend store managers to provide access (1) to electronic product information via a free wireless network infrastructure (e.g., WLAN) and (2) to products, which can be easily identified by RFID, barcodes or QR codes. This would not only enhance the retailer's competitive advantage as he or she attracts more consumers, which would otherwise find and purchase adequate products online at home, but this may also increase consumers' shopping experience in retail stores (Groeppel & Bloch, 1990). In this sense, retail stores add a unique selling proposition.

We further assume that there is the potential of a new market for companies to develop and sell MRAs for in-store purchase situations. The extension of physical products with product information services from several providers might change the way of retailing. New business models may consider extended product recommendation services such as digital product reviews (Kowatsch, Maass, & Fleisch, 2009) that are provided by user-communities (e.g., DooYoo, eOpinions or Ask.com) or professional magazines (e.g., PC Praxis, Car and Driver or Runner's World).

For providers of MRA technology and corresponding product services, another implication can be drawn from our subjects' feedback: it is crucial to provide fast product identification technologies and fast mobile applications, such that product information is presented (almost) without any delay to the end user. For instance, this can be done with an efficient interface to the camera of a mobile phone to identify products with barcodes or QR codes, e.g., by using Google's Android development kit or Apple's iPhone platform. But also interfaces to radio frequency devices as discussed in the current paper and which are also available in Nokia's NFC devices must be used with efficiency optimization in mind assuming the existence of products tagged with RFID antennas. Although some of these applications do already exist (Keegan, O'Hare, & O'Grady, 2008; Maass & Filler, 2006; Resatsch et al., 2008; von Reischach et al., 2009), they have two major shortcomings: they show a slow performance and lack mature graphical user interfaces that allow access to value added services such as product recommendation services or purchase transaction services that would further increase both perceived ease of use and perceived usefulness of a MRA.

6.3. Limitations

The current work is limited due to the preliminary character of the experiment and the use of a small sample that is not representative for consumers of retail stores in general. Thus, we found astonishingly clear results that are moderated by the fact that subjects were mostly technically savvy individuals. Additionally, consumers' self-consciousness of using a MRA in public retail stores was not tested in our experiment, but it may play a major role as discussed by Serif and Ghinea (2008). Hence, it is expected that individuals with less technical knowledge and little self-consciousness show smaller effects. Nevertheless, we want to make sure that at least technically savvy individuals adopt our MRA in purchase situations such that we are able to optimize the MRA and then conduct a more representative field study. Another shortcoming of our experiment lies in the subjects' motivation to perform the decision-making task, which was externally motivated rather than intrinsic. Thus, the utility of our MRA may be moderated by the degree of the task motivation of the participants as found by Chan (2009). In addition, our findings are based on the consumer electronics domain, in particular on mobile navigation units and accessories. Therefore, the research model needs to be tested for other products to add external validity. And finally, the perceived relevance of product information provided by a MRA when being compared to paper-based information in terms of alternative or complementary information channels was not covered by the current work but will guide future work as described in the following section.

7. Summary and future work

Product information influences product purchases and especially for online purchase situations, the value of product information is increased by the use of recommendation agents as information adapts dynamically to the interests and preferences of consumers. Because unprecedented, we investigated the use of mobile recommendation agents (MRAs) by means of an innovative product interface for product information acquisition in in-store shopping situations. Based on TPB, IDT and TAM we developed a theoretical model and tested it by conducting a lab experiment. Results demonstrate the usability and utility of our MRA implementation. We found that perceived usefulness of the MRA predicts its adoption, purchase intentions and store preferences, which is relevant for store managers in considering new kinds of business models that allow products to communicate with their consumers. Accordingly, the communication between consumers and products generate a new type of commercial situations in which the being of both consumer and product in a physical situation becomes an integral part of the commercial task environment.

This initial experiment deliberately focused at one particular instance of a MRA with a limited sample size. Thus, we will conduct a more representative field study, which also investigates the relation between paper-based product information and information provided by a MRA in terms of alternative or complementary information channels. Additionally, in another study, we compare different graphical user interfaces for one platform as well as from different platforms (e.g., Apple's iPhone vs. Nokia N97 vs. a Google Android mobile phone) that implement a MRA with various communication designs across different usage situations within the product life cycle. Here, the ease of use construct will be investigated further regarding its role to predict the behavioral intention to use MRAs. Another issue of future work is the determination and classification of relevant services that are required by consumers in purchase situations and have the potential to be provided through products. For instance, personalized grocery recommendations based upon consumer's allergies or dynamic pricing services for product bundles are relevant for both consumers' information needs and retailers' communication needs and can be provided on demand by products via MRAs.

Acknowledgements

This work was partially funded by the German Federal Ministry for Education and Research (BMBF) under the contract 1753X07. This work was also co-funded by the European Union under the contract ICT-231527. The authors thank Sabine Janzen and Andreas Filler for valuable discussions.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*, 179–211.
Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behaviour*. Inglewood Cliffs, NJ: Prentice Hall.
Bakos, J. Y. (1998). The emerging role of electronic marketplaces on the Internet. *Communications of the ACM, 41*(8), 35–42.
Barclay, D., Thompson, R., & Higgins, C. (1995). The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use an illustration. *Technology Studies, 2*(2), 285–309.
Baroudi, Jack J., & Orlikowski, Wanda J. (1989). The problem of statistical power in MIS research. *MIS Quarterly, 13*(1), 7–106.
Bitner, Mary Jo (1992). Servicescapes: The impact of physical surroundings on customers and employees. *Journal of Marketing, 56*(2), 57–71.
Bo, X., & Benbasat, Izak (2007). E-Commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly, 31*(1), 137–209.
Brooke, J. (1996). SUS: A "quick and dirty" usability scale. In P. Jordan, B. Thomas, B. Weerdmeester, & A. McClelland (Eds.), *Usability evaluation in industry*. London Taylor and Francis.
Chan, S. H. (2009). The roles of user motivation to perform a task and decision support system (DSS) effectiveness and efficiency in DSS use. *Computers in Human Behavior, 25*(1), 217–228.
Chin, W. W. (1998). Issues and opinion on structural equation modeling. *MIS Quarterly, 22*(1), vii–xvi.
Citrin, Alka Varma, Stem, Donald E., Jr., Spangenberg, Eric R., & Clark, Michael J. (2003). Consumer need for tactile input: An internet retailing challenge. *Journal of Business Research, 56*(11), 915.
Cohen, J. (1977). *Statistical power analysis for the behavioral sciences* (revised edition ed.). New York: Academic Press.
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–339.
Esslimani, Ilham, Brun, Armelle, & Bayer, Anne (2008). Behavioral similarities for collaborative recommendations. *Journal of Digital Information Management, 6*(6), 442–448.
Faul, Franz, Erdfelder, Edgar, Lang, Alber-Georg, & Buchner, Axel (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39*(2), 175–191.
Gefen, D., Straub, D., & Boudreau, M.-C. (2000). Structural equation modeling techniques and regression: Guidelines for research practice. *Communications of AIS, 7*(7), 1–78.
Gregor, Shirley, & Benbasat, Izak (1999). Explanations from intelligent systems: Theoretical foundations and implications for practice. *MIS Quarterly, 23*(4), 497–530.

Groeppel, Andrea, & Bloch, Brian (1990). An investigation of experience-oriented consumers in retailing. *International Review of Retail, Distribution & Consumer Research, 1*(1), 101.

Gurevych, Iryna, & Mühlhäuser, Max (2007). Natural language processing for ambient intelligence. *Künstliche Intelligenz, 2*, 10–16.

Hasan, B., & Ahmed, M. U. (2007). Effects of interface style on user perceptions and behavioral intention to use computer systems. *Computers in Human Behavior, 23*(6), 3025–3037.

Häubl, G., & Trifts, V. (2000). Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing Science, 19*(1), 4–21.

Junglas, Iris A., & Watson, Richard T. (2006). The U-constructs: Four information drives. *Communications of AIS, 2006*(17), 2–43.

Kamis, Arnold, Koufaris, Marios, & Stern, Tziporah (2008). Using an attribute-based decision support system for user-customized products online: An experimental investigation. *MIS Quarterly, 32*(1), 159–177.

Keegan, S., O'Hare, G. M. P., & O'Grady, M. J. (2008). EasiShop: Ambient intelligence assists everyday shopping. *Journal of Information Sciences, 178*(3), 588–611.

Kleijnen, Mirella, de Ruyter, Ko, & Wetzels, Martin (2007). An assessment of value creation in mobile service delivery and the moderating role of time consciousness. *Journal of Retailing, 83*(1), 33–46.

Komiak, Sherrie Y. X., & Benbasat, Izak (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly, 30*(4), 941–960.

Kourouthanassis, P., & Roussos, G. (2003). Developing consumer-friendly pervasive retail systems. *Pervasive Computing, 2*(2), 32–39.

Kowatsch, T., Maass, W., Filler, A., & Janzen, S. (2008). *Knowledge-based bundling of smart products on a mobile recommendation agent*. Paper presented at the IEEE 7th International Conference on Mobile Business (ICMB).

Kowatsch, T., Maass, W., & Fleisch, E. (2009). *The use of free and paid digital product reviews on mobile devices in in-store purchase situations*. Paper presented at the 4th Mediterranean Conference on Information Systems (MCIS 09).

Kurkovsky, S., & Harihar, K. (2006). Using ubiquitous computing in interactive mobile marketing. *Personal and Ubiquitous Computing, 10*(4), 227–240.

Lee, K. C., & Chung, N. (2008). Empirical analysis of consumer reaction to the virtual reality shopping mall. *Computers in Human Behavior, 24*(1), 88–104.

Maass, W., & Janzen, S. (2007). *Dynamic Product interfaces: A key element for ambient shopping environments*. Paper presented at the 20th Bled eConference. Available from: http://domino.fov.uni-mb.si/proceedings.nsf/2007.

Maass, W., & Kowatsch, T. (2008a). *Adoption of dynamic product information: An empirical investigation of supporting purchase decisions on product bundles*. Paper presented at the 16th European Conference on Information Systems (ECIS).

Maass, W., & Kowatsch, T. (2008b). *Mobile decision support vs. interpersonal sales communication: Predictors of buying intentions for price bundles*. Paper presented at the 21st Bled eConference.

Maass, W., & Filler, A. (2006). Towards an infrastructure for semantically annotated physical products. In C. Hochberger & R. Liskowsky (Eds.), *Informatik 2006* (pp. 544–549). Berlin: Springer.

Maass, W., & Varshney, U. (2008). *Preface to the focus theme section: 'Smart Products' electronic markets, 18*(3), 211–215.

Maidel, Veronica, Shoval, Peretz, Shapira, Bracha, & Taieb-Maimon, Meirav (2008). *Evaluation of an ontology-content based filtering method for a personalized newspaper*. Paper presented at the ACM conference on recommender systems.

McCabe, Deborah Brown, & Nowlis, Stephen M. (2003). The effect of examining actual products or product descriptions on consumer preference. *Journal of Consumer Psychology, 13*(4), 431–439.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2*, 173–191.

Nunnally, J. C. (1967). *Psychometric theory*. New York: McGraw-Hill.

Pereira, Rex Eugene (2001). Influence of query-based decision aids on consumer decision making in electronic commerce. *Information Resources Management Journal, 14*(1), 31.

Ponder, Nicole, Lueg, Jason E., & Williams, Zachary (2006). Salesperson assistance versus self-service in retailing: Are they both a matter of convenience? *Marketing Management Journal, 16*(1), 72–87.

Resatsch, Florian, Sandner, Uwe, Leimeister, Jan Marco, & Krcmar, Helmut (2008). Do point of sale RFID-based information services make a difference? Analyzing consumer perceptions for designing smart product information services in retail business. *Electronic Markets, 18*(3), 216–231.

Ringle, Christian Marc, Wende, Sven, & Will, Alexander (2005). SmartPLS (Release 2.0 M3) http://www.smartpls.de. University of Hamburg, Hamburg, Germany.

Rogers, E. M. (2003). *Diffusion of innovations* (fifth ed.). New York: Free Press.

Serif, T., & Ghinea, G. (2008). Mobile information access in the real world: A story of three wireless devices. *Computers in Human Behavior, 24*(4), 1385–1403.

Stahl, F., & Freudenschuss, M. (2006). *Mobile business through RFID technology: About the potential of RFID technology for distributing free and paid content on mobile devices in retail business*. Paper presented at the Americas Conference on Information Systems.

Tellis, Gerard J., & Gaeth, Gary J. (1990). Best value, price-seeking, and price aversion: The impact of information and learning on consumer choices. *Journal of Marketing, 54*(2), 34–45.

Todd, Peter, & Benbasat, Izak (1999). Evaluating the impact of DSS, cognitive effort, and incentives on strategy selection. *Information Systems Research, 10*(4), 356–374.

van der Heijden, Hans (2006). Mobile decision support for in-store purchase decisions. *Decision Support Systems, 42*(2), 656–663.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

von Reischach, F., Guinard, D., Michahelles, F., & Fleisch, E. (2009). *A mobile product recommendation system interacting with tagged products*. Paper presented at the seventh annual IEEE international conference on Pervasive Computing and Communications (PerCom 2009).

Watson, Richard T., Pitt, Leyland F., Berthon, Pierre, & Zinkhan, George M. (2002). U-commerce: Expanding the universe of marketing. *Journal of the Academy of Marketing Science, 30*(4), 333–347.

Westerman, S. J., Tuck, G. C., Booth, S. A., & Khakzar, K. (2007). Consumer decision support systems: Internet versus in-store application. *Computers in Human Behavior, 23*(6), 2928–2944.

Yang, Jin-Min, Li, Kin Fun, & Zhang, Da-Fang (2009). Recommendation based on rational inferences in collaborative filtering. *Knowledge-Based Systems, 22*(1), 105–114.

Youll, J., Morris, J., Krikorian, R., & Maes, P. (2000). *Impulse: Location-based agent assistance*. Paper presented at the fourth international conference on autonomous agents.

Zhang, Xiangmin, & Li, Yuelin (2008). Use of collaborative recommendations for web search: An exploratory user study. *Journal of Information Science, 34*(2), 145–161.

Zhenhui, Jiang, & Benbasat, Izak (2004). Virtual product experience: Effects of visual and functional control of products on perceived diagnosticity and flow in electronic shopping. *Journal of Management Information Systems, 21*(3), 111–147.