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The Determinants of Acceptance of Recommender Systems: Applying the UTAUT Model

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ABSTRACT

This study investigates how consumers assess the quality of two types of recommender systems, collaborative filtering and content-based, in the content of e-commerce by using a modified Unified Theory of Acceptance and Use of Technology (UTAUT) model. Specifically, the under-investigated concept of trust in technological artifacts is adapted to a modified UTAUT model. Additionally, this study considers hedonic and utilitarian product characteristics, attempting to present a comprehensive range of recommender system acceptance. A total of 51 participants completed an online 2 (recommender systems) x 2 (products) survey. The results suggested that type of recommender systems and products did have different impacts on the behavioral intention to use recommender systems. This study may be of importance in explaining factors contributing to use recommender systems, as well as in providing designers of recommender systems with a better understanding of how to provide a more effective recommenders system.

Keywords

Recommender systems, UTAUT, trust, hedonic product, utilitarian product.

INTRODUCTION

Two types of recommender systems, collaborative filtering and content-based, have been increasing implemented as a support tool for customers improving the quality of purchasing decisions and solving information overload (Grenci and Todd, 2002; Keefe and Mceachem, 1998; Liang, 2008; Scjafer, Konstan, and Riedl, 2001). These two types of systems have dramatically different algorithm to generate recommendations. Prior works have been focused almost exclusively on the improvement and development of the algorithms to provide more efficient and accurate recommendations (Goldberg, Nichok, Oki, and Terry, 1992; Yuan and Tsao, 2003). However, little is known with respect to why people want to use these two types of recommender systems to improve their purchasing decisions. As the dependency on recommender systems in e-commerce increases rapidly, so does the need to realize factors associated with utilizing recommender systems. Therefore, guided by Venkatesh, Morris, Davis, and Davis's study (2003), this study tries to answer the following first set of questions: what are major determinants to accept two types of recommender systems and would people have any different perceptions to accept these two types of recommender systems?

Trust is seem as an antidote to risk by inexperienced online customers and a reducer of social uncertainty in e-commerce (Gefen, 2000; Gefen, Karahanna, and Straub, 2003a, 2003b; Gefen and Straub, 2004). As an attempt to provide the most customized recommendations, the recommender systems need to inquire customers' personal information such as their preferences or browsing behaviors to help them to improve their purchasing decisions. As a result, it is important to know the effect of trust on affecting people to accept two types of recommender systems. This study combines the concept of trust with a modified UTAUT model to answer the following second question: does trust matter in affecting people to accept two types of recommender systems.

Over the last few decades, within the field of marketing and customer research, two types of products, utilitarian and hedonic products, have been shown to have different effects on customers' use of personal information and their choices (Bearden and Etzel, 1982; Childers and Rao, 1992; Wertenbroch and Dhar, 2000;). What remains to be explored in research associated with recommender systems, however, are whether two types of products have different impacts on affecting customers to accept two types of recommender systems. Considering the different characteristics of two types of products in affecting customers' purchasing decisions, this study takes into account utilitarian and hedonic products to represent a comprehensive study of accepting recommender systems.

In conclusion, the specific purposes of this study are: (1) to examine UTAUT relevance toward accepting collaborative filtering and content-based recommender systems, (2) combine the concept of trust with a modified UTAUT model to establish a comprehensive understanding of recommender system acceptance, and (3) examine potential differences of two types of products, hedonic and utilitarian, in affecting customers to accept recommender systems.

LITERATURE REVIEW

Recommender Systems

Recommender systems evolved in response to the choice and information overload to consumer and combine with consumer frustrating at a decreasing level of professional support for making these choices (Burke, 2002; Konstan, 2004; Resnick and Varian, 1997). With this purpose, recommender systems have been implemented widely in any size of e-commerce Web sites (Amazon.com, eBay, Dell, Shopping.com, and so on) to better serve their customers and increase sales. Generally, two recommender systems have come to dominate: collaborative (social) filtering and content-based/attribute-based (Adomavicius and Tuzhilin, 2005; Cosley, Lam, Albert, Konstan, and Riedl, 2003). These two systems have their own pros and cons. A hybrid recommender system makes an appearance to combine these two technologies to gain better performance with fewer of the drawbacks (Burke, 2002).

Collaborative Filtering Recommender System

The collaborative filtering recommender system predicts a person's preference as a weighted sum of other's preferences, in which the weights are proportional to correlation over a common set of items rated by two customers (Adomavicius and Tuzhilin, 2005; Ansari, Essegaier, and Kohli, 2000; Konstan, 2004; Konstan, and Riedl, 2003). It is motived by the observation that in reality we often look to our friends for recommendations. In order to make predictions reasonably, the assumption of the collaborative filtering is that people with similar preferences will rate thing similarly (Schafer, Frankowski, Herlocker, and Sen, 2007). The greatest of the collaborative filtering is that it is completely independent of any machine-readable representation of the objects being recommended, and works well for complex object such as music and movies (Burke, 2002).

Content-based Recommender System

Content-based systems analyze item descriptions and user profiles to identity items that users may like (Ansari et al., 2000; Balabanovic and Shoham, 1997; Pazzani and Billsus, 2007). Specifically, this system selects items to recommend based on the correlation between the content of items and users' preferences. Content-based uses the assumption that items with similar features will be rated similarly (Adomavicius and Tuzhilin, 2005). Because the content-based system makes the recommendations from only customers' personal preferences, customers may not feel surprising for the results of recommendations (Adomavicius and Tuzhilin, 2005; Konstan, and Riedl, 2003). To conclude, if the collaborative filtering recommendation system is a system that recommends similar "users" to the user preferences, the content-based recommender system is a system that recommends similar "items" to the user preferences.

Unified Theory of Acceptance of Use of Technology (UTAUT)

One of continuing issues in the field of information system is to identify factors that cause people accept and use of systems developed and implemented by others. Proposed by Davis (1989), Technology Acceptance Model (TAM) is a well-validated model in predicting and explaining users' intention to accept technology. Extending Davis's study (1989) and integrating eight related models, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT). They identified four constructs as major determinants of people's behavioral intentions and actual behaviors in technology acceptance: performance expectancy, effort expectancy, social influence, and facilitating conditions. Additionally, gender, age, experience, and voluntariness of use are believed to moderate the impacts of these determinants on the usage intention and behavior. A modified UTAUT model was used to examine factors associated with the intention of accepting recommender systems.

Trust

Customers often hesitate to interact with web-based vendors because of uncertainty of performance behaved by these vendors or perceived risk of personal information stolen by hackers (McKnight, Choudhury, and Kacmar, 2002). When people cannot reduce social uncertainty through rules or customs such as an online environment, they resort to trust as a major method to reduce social uncertainty (Luhmann, 1979; Thibaut and Kelley, 1978). Trust is an expectancy that others one chooses to trust will not behave opportunistically by taking advantage of the situation (Gefen et al., 2003b; Geyskens, Steenkamp, Scheer, and Kumar, 1996). Prior works have studied more on applying the concept of trust into the acceptance of e-commerce, showing that trust does influence people's intentions to purchase. Privacy is a particularly important concern for consumers of e-vendors. In the setting of recommender systems, customers should trust providers of recommender systems that they will not take advantage of customers' vulnerabilities and expose their personal information (privacy concern). As a consequence, trust was integrated the modified UTAUT model to examine its impact on the intentions of affecting people to accept two types of recommender systems.

Types of Products

Previous researches have demonstrated that hedonic and utilitarian products have different effects on customer behaviors and attitudes (Bearden and Etzel, 1982; Childers and Rao, 1992; Heijden, 2004; Hirschman and Holbrook, 1982; King and Balasubramanian, 1994; Wertenbroch and Dhar, 2000). Hedonic product provides more experiential consumption, pleasure, fantasy, fun, and excitement, whereas utilitarian product is instrumental, functional, and goal oriented (Hirschman and Holbrook, 1982; Wertenbroch and Dhar, 2000). Therefore, this study investigates hedonic and utilitarian product characteristics to determine their potential differences on customer use of recommender systems.

RESEARCH MODEL AND HYPOTHESESE

Research Model

As discussed above, our research model posits that some characteristics of UTAUT, performance expectancy, effort expectancy, and social influence, and trust facilitate behavioral intention to use recommendation systems. Figure 1 presents the research model of this study.

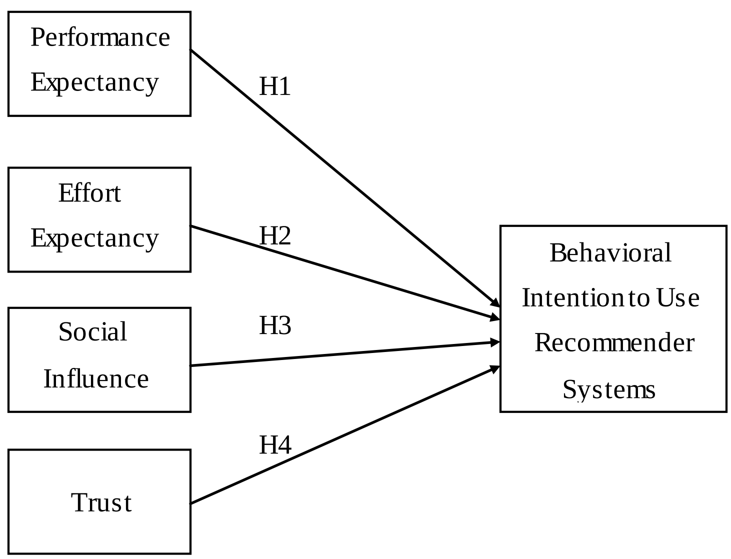

Figure 1. Research Model

Definitions of Key Concepts

To avoid possible confusion, key concepts presented in the proposed framework are defined in this section.

Performance Expectancy

Performance expectancy to the recommender system is defined as the degree to which an individual believes that using the recommender system will help him or her to increase the efficiency of searching or finding items (e.g., improving the quality of purchasing decisions, solving the problem of information overload).

Effort Expectancy

Effort expectancy to the recommender systems is defined as the degree of ease associated with the use of the recommendation system (e.g., easy to express personal preference, easy to check or select the recommended results).

Social Influence

Social influence to the recommender systems is defined as the degree to which an individual perceives that important others such as peers, families, friends, professors, or colleagues believe he or she should use the recommendation system.

Trust

Trust to the recommender system is defined as the degree to which an individual believes that recommender agents can be relied on and will not take advantages of the customers' vulnerabilities when users request the recommendation.

Behavioral Intention to Use Recommender Systems

The behavioral intention to use the recommender systems is defined as a person's readiness to use the recommender systems to receive purchasing advices.

Research Hypotheses

Previous studies show that performance expectancy is the strongest predicator of intention in accepting or rejecting a technology (Davis, 1989; Davis, Bagozzi, and Warshaw, 1989; Venkatesh and Davis, 2000; Venkatesh et al, 2003). Thus, Hypothesis 1 can be proposed as:
H1. Performance expectancy of the recommender system will positively influence people's intentions to accept recommender systems.

Effort expectancy shows positive effect to influence people to accept or reject a technology (Davis, 1989; Venkatesh et al, 2003). A technology perceived to be easier to use than another is more likely to be accepted by the user (Davis, 1989). Therefore, Hypothesis 2 can be proposed as:
H2. Effort expectancy of the recommender system will positively influence people's intentions to accept recommender systems.

Prior studies have stated that social influence is a direct determinant of behavioral intention, that is, people's behavioral intention will be influenced by their peers, families, or friends (Ajzen, 1992; Moore and Benbasat, 1991; Venkatesh and Davis, 2000). As a result, Hypothesis 3 can be proposed as:
H3: Social influence will positively influence people's intentions to accept recommender systems

Trust has been empirically validated as one of the most important determinants to purchase intention by online shoppers (Gefen, 2000; Gefen et al., 2003a, 2003b; Gefen and Straub, 2004). Potential buyers must also believe in the predictability of the e-vender. In other words, customers' trust to e-vendor can reduce their concerns in the risk of exposing privacy issues (Gefen et al., 2003a, 2003b). Recommender systems involve in inquiring customers' personal information to make recommendations. Thus, if users of recommender system believe that the providers of recommender system may make inappropriate use of personal information, they are not likely to use recommender systems. To summarize, Hypothesis can be contented as:

H4. Higher level of the customer trust to the providers of recommender systems will lead to high intentions to use recommender systems.

PROCEDURES

Pilot Test

A pilot test was conducted first to find suitable products to be utilized in the primary studies. 27 undergraduate students from a large Midwestern university in the United States were asked to evaluate a set of products classes: cell phones, laptop computers, desktop computers, digital cameras, MP3 players, TVs, camcorders, printers, and GPSs. MP3 players represented the most hedonic product class (mean=2.17), and printers represented the most utilitarian (mean=5.05). Furthermore, paired sample t-test also showed a significant difference between the MP3 player and the printer (t =-8.96, p<0.001, CI= [-3.55, -2.33]).

Primary Study

Subjects involved in the primary study consisted of 51 undergraduate students from a large Midwestern university. Participants in the pilot and the primary study were voluntary and students were rewarded extra credits in the course for taking part in this study. The primary study conducted a 2x2 crossover within subject experimental design for measuring difference between 4 treatments. The experiment was constructed as follows: $X_1O_1X_2O_2X_3O_3X_4O_4$. The four different treatments (X_1–X_4) were presented to each subject in a random order and subsequent observations (O_1–O_4) were taken after each treatment. Each treatment (X) consisted of the subject simulating the buying an item on a website based on the recommender system where the recommender system type and product type were randomly delivered. Therefore, the subject bought a hedonic product using a collaborative-based recommender system, a utilitarian product using a collaborative-based recommender system, a hedonic product using a content-based recommender system, and a utilitarian product using a content-based recommender system. The subject performed each task (X) separately followed by the subject filling out the same questionnaire (O) for each task. The lack of learning effects and randomization of the treatments allowed the researchers to increase power by utilizing the same subjects for all four treatment groups while controlling for history effects by randomizing the treatment order. During the treatments, subjects were requested to navigate through two types of recommender systems before filling in the experimental instrument. An online survey was used to administer each treatment and collect individual response. Shopping.com (http://www.shopping.com/) was used for the collaborative filtering recommender system treatments and CNET Reviews (http://reviews.cnet.com/) was used for the content-based recommender system treatments. MP3 players were selected as the hedonic product and printers were used as the utilitarian product.

Measurement

A questionnaire was created with items validated in prior research adapted to the technologies and trust studies. Scales of PE, EE, and SI were adapted from Venkatesh et al. (2003). Validated trust scales were adapted from Gefen (2000).

RESULTS

Partial lest square (Visual PLS, Version 1.04) was used to examine the reliability and validity test. PLS is especially suited for exploratory research, such as the current study (Chin, 1998; Gefen, 2003; Gefen, Straub, and Boudreau, 2000). The loading of items was found to be acceptable with most items .70 or higher except the SI3s from the treatment 1 and 2, respectively. These two items were dropped before examining the structural model. All internal consistency reliabilities for four treatments were higher than .70. PLS was used to test four treatments and a pooled case. We employed a boots trapping method (200 times) that used randomly selected subsamples to test the PLS model. The Chow's test was conducted to determine legitimacy of pooling. The results indicated that the pooled data can be used to examine the combined model. Table 1 summarizes the model test results from four treatments and the pooled case.

DV: Behavioral Intention to Use Recommender Systems					
	Treatment 1 (N=51)	Treatment 2 (N=51)	Treatment 3 (N=51)	Treatment 4 (N=51)	Pooled (N=204)
R^2 (PLS)	.49	.31	.51	.62	.42
PE	**.46****	.37	.06	.14	**.27****
EE	.06	.11	.14	.16	**.13***
SI	-.06	.24	**.39****	**.31***	**.16***
Trust	**.34***	-.10	.26	**.29***	**.22***

Table 1. Results of the Tested Mod

Notes:

1. * p <.05; ** p <.01; *** p<.001
2. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence;
3. Treatment 1: Content-based recommender system with the hedonic product (MP3 player);

Treatment2: Content-based recommender system with the utilitarian product (printer);

Treatment3: Collaborative filtering recommender system with the hedonic product (MP3 player)
Treatment4: Collaborative filtering recommender system with the utilitarian product (printer)

For the treatment 1, the content-based systems with the hedonic product, the results indicate that performance expectancy (PE) and trust had significant impacts on the behavioral intention (BI) to use recommender systems (ß =0.46, $p < 0.01$; ß =0.34, $p < 0.05$), supporting H1 and H4. Contrary to expectations, effort expectancy (EE) and social influence (SI) had no impacts on the behavioral intention, thereby providing no support for H2 and H3. For the treatment 2, the content-based system with the utilitarian product, all hypotheses were not confirmed, indicating that types of products have different effects in influencing people's intentions to recommender systems.

For the treatment 3, the collaborative filtering system with the hedonic product, social influence (SI) had a significant impact on the behavioral intention to use recommender systems (ß =0.39, $p < 0.01$), supporting H3. However, H1, H2, and H4 were not confirmed. For the treatment 4, the collaborative filtering system with the utilitarian product, social influence (SI) and trust had significant effects on the behavioral intention to use recommender systems (ß =0.31, $p < 0.05$; ß =0.29, $p < 0.05$). Again, the results from the treatment 3 and 4 indicated that types of products have different effects in influencing people's intentions to use recommender systems.

Examining the results from the treatment 1 and 3 (the content-based systems and the collaborative filtering systems with the hedonic product), we can realize that types of recommender systems have different effects in influencing people's intentions to use recommender systems. Again, the results from the treatment 2 and 4 (the content-based systems and the collaborative filtering systems with the utilitarian product) also support our argument: the collaborative filtering and the content-based recommender system have different effects in affecting people's behavioral intentions to use recommender systems. For the pooled case of four treatment (N=204), all hypotheses were supported with a R^2 of 42%. The result from the pooled case can imply to the setting of the hybrid recommender system in which performance expectancy (PE), effort expectancy (EE), social influence (SI), and trust (Trust) are critical factors to affect people's behavioral intentions to accept the hybrid recommender system.

CONCLUSION

Discussion

Our study presented and validated a modified UTAUT model to help in understanding factors contributing to use two types of recommender systems in the setting of e-commerce. Concerning with different effects of the hedonic and utilitarian products (MP3 player and printers in this study) in affecting people's purchasing decisions, we also took into account of hedonic and utilitarian characteristics to determine their effects on the customer acceptance of recommender systems. With empirical analysis, we may reasonably conclude that different types of recommender systems and products do have different effects in influencing people's behavioral intentions to use. Specifically, our findings are no in contradiction with those of technology acceptance related studies discussed above. Like the original UTAUT study, the study showed statistical significance on the proposed effects of PE on BI in the treatment 1 (the content-based system with the hedonic product) and the pooled case. A general interpretation for there being no statistical significance of PE on BE in the rest of treatments may lie in fundamental differences of two types of recommender systems and products.

For the proposed effect of EE on BI, there was a lack of statistical significance in four treatments except for the pooled case. One reason to account for this may lie in the fact that most of participants showed a medium or high degree of experience using recommender systems. The effect of effort expectancy is significant during the first time period of accepting the technology; however, it becomes non-significant over period of extended and sustained usage (Venkatesh et al., 2003). Thus, the findings of the current study are in line with the previous study.

The findings of our study provide interesting insights for the effect of SI on BI. Our data suggested that SI does matter in the setting of the collaborative filtering recommender system regardless of types of products and the pooled case. Social influence plays a more important role for collaboration technologies because they are social technologies (Brown, Dennis, and Venkatesh, 2010). These results are consistent with prior studies associated with the collaborative technology. Therefore, it is apparent that a potential user of the collaborative filtering recommender system may use this system due to the reason, such as important others believe he or she should use the new system. On the other hand, the same reason may not impact on those who use the content-based recommender system.

Trust is emerging as an important aspect of technology acceptance as an interesting number of technologies engage in privacy issue over the web. However, trust has not been examined very much in the widely used models explaining technology acceptance such as the UTAUT. The study contributes to explanatory model of trust by adding the concept of trust to a modified UTAUT model. Data from the study leads us to believe that providers of online recommender systems should notice the importance of trust. Trust appeared to play an important role in both types of recommender systems. It is noteworthy that trust had significant effects on the content-based recommender system with the hedonic product and the collaborative filtering recommender system with the utilitarian product, aligning with our argument again: two types of recommender systems and products have different effects in affecting people's behavioral intentions to accept recommender systems. Additionally, trust also had an significant impact in the pooled case, indicating that trust will be a critical factor for those who design hybrid recommender system. To conclude, this result implies that a customer's intention to use recommender systems depends not only on the operational characteristics of the recommender systems, its performance expectancy (PE) or effect expectancy (EE), but also, and possibly to a greater degree, on customer trust for the providers of recommender systems. Providers of these systems need to take into account their recommenders planning efforts.

From a theoretical perspective, this study contributes to the field's understanding of the various factors in influencing people's behavioral intentions to use recommender systems as they as the issue of information overload in the setting of e-commerce. The results of this study support the relevance of the UTAUT in accepting online recommender systems. This study also suggests a new perspective for the UTAUT model in general. In this line of research, research focus more on expected outcome of operational characteristics, such as performance expectancy or effort expectancy. The concept of trust did not show up very often in this line of research. Due to highly competitive environment, more and more providers of the innovative technologies try to provide the most customized services to maintain competitive advantage in online environment. However, because of high uncertainty for providers of technologies, users may not intend to use these technologies until they trust these provides. Thus, the concept of trust should be taken into consideration with the model associated with technology acceptance. By integrating the concept of trust with a modified UTAUT model, this study represents a step forward in the overall model development. This study has important practical implications for designers of effective online recommender systems. The findings of this study indicate that participants had different perceptions for two types of recommender systems.

PE and Trust are two major concerns for those who use the content-based system. On the other hand, SI and Trust are another two major concerns for those who use the collaborative filtering recommender system. Thus, manager should realize fundamental differences of two types of recommender systems and make appropriate strategies when they try to invest on building an effective recommender system. Additionally, although effort expectancy (EE) was lack of statistical significant except the pooled case, managers cannot make light of the importance of effort expectancy. Designers should consider and provide a friendly environment for those first time users or users who do not have so many experiences using recommender systems. Managers or designers should treat this part of results. The ultimate goal of recommender systems is to help customers find the most appropriate products and then bring more profits to provide of recommender systems. Trust appears to an important role for both types of recommender systems. Thus, designers must design a recommender system in which customers believe that the providers of this system will not take advantage of their weakness.

Limitations and Future Research

Even though this study has the undeniable merit of offering valuable insights into the process of recommender systems acceptance, it has some limitations. First, the study investigated participants who were working on undergraduate degree. The generalization of the results to other populations with different educational backgrounds may be limited. Thus, more replications to test our model in other population are necessary to examine our findings. Secondly, since the study analyzed recommender systems from two well-known websites, it is unclear whether the results can be generalized to less-known websites. A replication of this study needs to take into considerations this issue. This study only investigated people's intentions to use recommender systems. No actual behavior was measured in this study. Perhaps future research could examine the interaction between behavioral intention and actual behavior. Additionally, as described above, a future research should also consider and analyze less-known websites to achieve the goal of generalizability.

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