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Antecedents of Review and Recommendation Systems Acceptance

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ABSTRACT

Online recommendation systems, which are becoming increasingly prevalent on the Web, help reduce information overload, support quality purchasing decisions, and increase consumer confidence in the products they buy. Researchers of recommendation systems have focused more on how to provide a better recommendation system in terms of algorithm and mechanism. However, research which has empirically documented the link between customers' motivations and intentions to use recommendation systems is scant. Therefore, the aim of this study attempts to explore how consumers assess the quality of two types of recommendation systems, collaborative filtering and content-based 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 the UTAUT model.

In addition, this study considers hedonic and utilitarian product characteristics, attempting to present a comprehensive range of recommendation systems. A total of 51 participants completed an online 2 (recommendation systems) x 2 (products) survey. The quantitative analysis of the questionnaires was conducted through multiple regression and path analysis in order to determine relationships across various dimensions.

Results of this study showed that types of recommendation systems and products did have different effects on behavioral intention to use recommendation systems. To conclude, this study may be of importance in explaining factors contributing to use recommendation systems, as well as in providing designers of recommendation systems with a better understanding of how to provide a more effective recommendation system.

CHAPTER 1. OVERVIEW

The recommendation system is an electronic aid that helps people make purchasing decisions, solves the problem of information and choice overload, and finds the most personalized products based on their browsing history, rating records, or purchasing records in the world of E-Commerce. This system has been seen as an important marketing tool to enhance E-Commerce (Schafer, Konstan, &Riedl, 2001). In the past two decades, many IS researchers have studied the topic of technology acceptance (Gefen &Straub, 1997; Hsu &Lin, 2008; Koufaris, 2002; Mathieson, 1991; Terveen &Hill, 2001; Venkatesh, 2000), which was introduced first by Davis (1989). Based on Unified Theory of Acceptance and Use of Technology proposed by Venkatesh et al. (2003), this study examines possible factors influencing people's intentions to accept recommendation systems in the realm of e-commerce.

1.1 Background

With the rapid propagation of the Internet, the market of e-commerce has grown globally at a tremendous pace in the past few years. According to the U.S. Department of Commerce, the value of sales revenue from e-commerce in 2008 was US$22.4 billion. This amount includes both business-to-business (B-to-B) and business-to-consumer (B-to-C). Additionally, according to eMarketers' annual report of 2006, the e-commerce market in Europe has reached 106 billion EURO ($133 billion US dollars). Analysts say that this situation will be stable for at least five years and the market will reach the point of 323 billion EURO ($407 billion US dollars) by 2011. However, this expansion has been accompanied by consumer frustration due to information overload and the perception of too many choices. Although e-commerce provides a virtually limitless shopping platform for customers, sometimes people still feel frustrated because of information and choice overload. They need to spend a lot of time comparing and evaluating the functionality and prices of various items before making purchasing decisions. From the customer's perspective, purchasing is a time-consuming job. By screening out unsuitable choices, recommendation systems have been seen as a support tool for customers during the process of making purchasing decisions (Grenci &Todd, 2002; Keefe &Mceachern, 1998; Maes, Guttman, &Moukas, 1999), helping them improve the quality of purchasing decisions and increase their confidence in products they choose (Haubl &Trifts, 2000; Hostler, Y., &Guimaraes, 2005; Lee &Lee, 2004; Riecken, 1994).

In addition, from the perspective of the providers of recommendation systems, recommendation systems play an important role to increase e-commerce sales. Schafer, Konstan, and Riedl (2001) pointed out that the recommendation system enhances e-commerce sales in three ways: (1) converting browsers into buyers (2) increasing cross-sell, and (3) building loyalty. Prominent e-commerce Web sites (Amazon.com, ebay, Dell, iQVC, onSale, Walmart, Circuit city, Guitar Center, Shopping.com, and so on) showed a wide degree of implementation in recommendation systems. Overall, recommendation systems have become a required factor in building a successful and profitable e-commerce Web site.

1.2 Research

Starting from Goldberg et al. (1992), scholars focused more on how to provide a better recommendation systems in terms of algorithm and mechanism (Sarwar, Karypis, Konstan, &Riedl, 2000; Wang, F.-H. &Shao, 2004; Yuan &Tsao, 2003). What remains to be explored, however, are why people are willing to use recommendation system and what factors influence their use of these systems. Specifically, two types of recommendation systems, collaborative filtering and content-based, have been implemented largely to enhance e-commerce sales. As the dependency on recommendation systems in e-commerce increases rapidly, so does the need to realize factors associated with people to use recommendation systems.

Seminal work on the Technology Acceptance Model (TAM) was carried out by Davis (1989), still the reference point for virtually all discussions of technology acceptance and related applications. With vigorous development in technology acceptance, Venkatesh et al. (2003) used the concept of TAM, along with eight related theories, and developed the Unified Theory of Acceptance and Use of Technology (UTAUT) to predict technology acceptance decisions. Although there has been a dramatic proliferation of research concerned with the reliability and validity of the UTAUT in recent years (Anderson, J. E. &Schwager, 2004; Hennington &Janz, 2007; Marchewka, Liu, &Kostiwa, 2007; Wills, El-Gayar, &Bennett, 2008), we did not find any publications that examined factors associated with using online recommendation systems by using the UTAUT. Hence, in order to help fill this gap in our knowledge, this study investigates the acceptance of online recommendation systems by using a modified UTAUT model.

In addition to UTAUT, trust is seen as an antidote to risk by inexperienced online customers and a reducer of social uncertainty (Gefen, 2000; Gefen &Straub, 2003; Jarvenpaa, Tractinsky, &Vitale, 2000). Trust is an important issue in the adoption of new technology (Fukuyama, 1995), including e-commerce (Gefen &Straub, 2000). Thus, by combining the concept of trust and UTAUT, we further our understanding of why people might accept recommendation systems in e-commerce.

The type of product has been shown to affect customers' use of personal information source and their choices (Bearden &Etzel, 1982; Childers &Rao, 1992; King &Balasubramanian, 1994). Specifically, there are two types of products, hedonic and utilitarian (Dhar &Wertenbroch, 2000). These two types of products are used as moderating influences to examine if they have different effects on the process of accepting recommendation systems.

The major purpose of this study is to examine the relevance of UTAUT in accepting two types of recommendation systems, collaborative filtering and content-based, in e-commerce. The specific aims in this study are to combine the concept of trust with the UTAUT model and to measure possible differences of two types of products in accepting two types of recommendation systems.

To address the issues already outlined and to begin to fill the gaps in the previous research, the present study is designed address the following research questions: (1) What factors influence people's intention to use the two types of recommendation systems, collaborative filtering or content-based, by using a modified UTAUT? (2) Do these two types of recommendation systems have different effects on people who use them? If yes, what factors may explain these differences? (3) For two types of products, hedonic and utilitarian, do they have different effects to influence people to adopt two types of recommendation systems? (4) And finally, can the concept of trust integrate well with the UTAUT model to explain the comprehensive picture of adopting recommendation systems?

This study concludes with implications for theory, research, and practice. For academics, this study may be critically important in laying the groundwork for understanding how suitable and reliability of the UTAUT is in accepting two types of recommendation systems in e-commerce. It may also lead to a better understanding of trust in fitting with the original UTAUT model. Additionally, this study may serve as a basis for those e-venders who want to realize customer's behaviors and implement recommendation systems to increase market share. This study is done with hope that it may provide practitioners with better knowledge needed to design a better recommendation system. With the result of this study, hopefully, the system can be more effective, customized and hence will likely enhance more e-commerce sales in the long term.

The next section of this thesis elaborates on the theoretical foundations of the study and the hypotheses. The method and procedure are then described, followed by the results of this study. The final section provides concluding summary and discussion.

CHAPTER 2. REVIEW OF LITERATURE

The purpose of this chapter is to organize related theory and then build a comprehensive theoretical framework. This research aims to explore people's intentions or motivations to accept content-based and collaborative filtering recommendation systems. One the one hand, by realizing the fundamental differences of these two systems, this research examines people's intentions in these two individual cases. On the another hand, by combining the UTAUT and the concept of trust, this research hopes to integrate any potential factor contributing to people's intentions to accept the recommendation system.

2.1 Recommendation Systems

2.1.1 An Overview of Recommendation Systems

Imagine a real case in the bookstore where you have a personal preference for a specific genre in your mind, but you have no idea which book is the best choice for you especially when you face a bunch of similar books in the bookshelf. At this time, you probably will ask the store assistance for further suggestion to find the most appropriate book. In everyday life, it is often necessary to make decisions for many unknown situations without adequate personal experiences. We seek recommendations from people who are very familiar with the choices, or who are recognized as the expert to help us solve out this unclear situation. Resnick and Varian (1997) has stated that "recommender systems assist and augment this natural social process". Recommendation system evolved in response to the choice and information overload to consumer and combined with consumer frustrating at a decreasing level of professional support for making these choices (Schafer et al., 2001). Thus, what is the definition of recommender system? A variety of definitions are given in the literature for recommendation systems. Table 1 presents these various definitions by different researchers or organizations.

Table 1. Definitions of the recommendation system

Researcher	The Definition of Recommendation System
Breese, Heckerman, and Kadie (1998)	Collaborative filtering or recommender systems are a system that uses a database about user preference to predict additional topics or products a new user might like.
Meteren and Someren(2000)	Recommender systems are a special type of information filtering systems that deal with the delivery of items selected from a large collection that the user is likely to find interesting or useful and can be seen as a classification task.
Burke(2002)	Recommender system is a system which has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options.
Konstan(2008)	Recommender systems help individuals manage a potentially overwhelming set of choices by suggesting specific information, product, or people to those individuals based on the systems' knowledge of the individual's preferences and/or current need, and the collected knowledge of preferences within the larger community of system users.
Ting-Peng Liang(2008)	A recommendation system is an information system that is capable of analyzing previous user behavior and making recommendations for solving new cases.

Although the original purpose of recommendation system was not used in e-commerce, recently, because of the special attribute of recommendation systems in information filtering, recommendation systems have been implemented widely in any size of e-commerce Web site to address the result of providing mass customizations, explosive choices and information (Ansari, Essegaier, &Kohli, 2000; Linden, Smith, &York, 2003).

They can help businesses to decide whom to make an offer, achieving the goal of one-to-one marketing strategy. For example, customers searching through the NBA section at Yahoo may receive a banner advertisement for SportAuthority.com, while customers navigating to the directory of education may receive an advertisement from University of Phoenix. Basically, in a recommendation system setting, a recommendation seeker can ask for recommendation or the system can provide the recommendation without prompting e.g., Bestsellers in Amazon.com. In order to get the personalized recommendation in the first case, seekers may specify their preferences by rating some specific items provided by the system. Recommendation systems will analyze these preferences to overcome the limitations of segment-based mass marketing by presenting each customer with a personal set of recommendations. Figure 1 shows the basic process of recommendation systems.

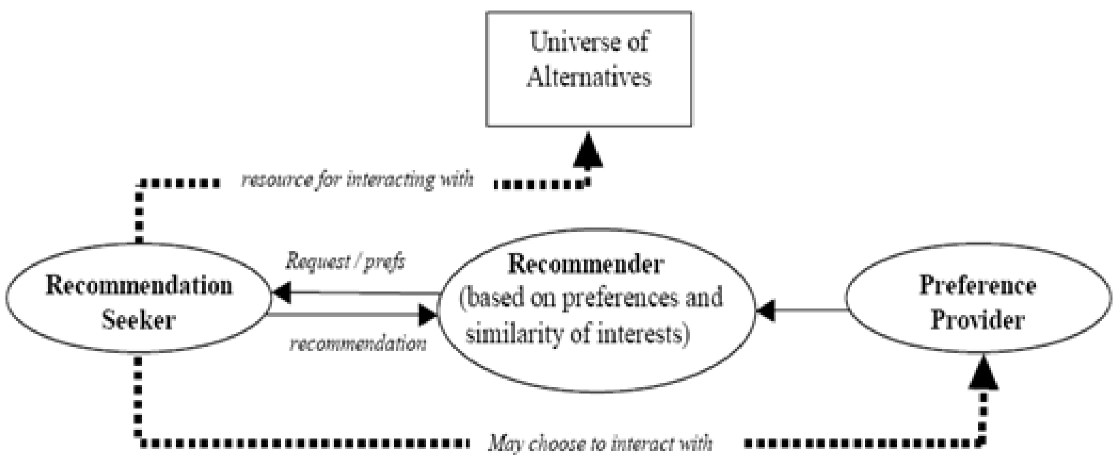

Figure 1. Model of the recommendation process, Terveen and Hill (2001)

Liang and Lai (2002) stated that customer profile is the key to information filtering and recommendation. Basically, user preferences, user behavior patterns, or item properties are three possible categories in the customer profile. Recommendation systems use two ways to learn and build customer profile through feedback, implicit and explicit (Meteren &Someren, 2000; Oard &Kim, 1998; Zhang &Seo, 2001). In explicit case, the system asks the user to express their preferences or choices explicitly and uses this information for the future recommendations. For example, users may rate an item as “good” or “bad” or indicate the interest level from one to five. Although this method is the most effective way to get customer's preference, few drawbacks still exist in this strategy: (1) the user has to participate in providing relevance feedback, creating more burdens for them, and (2) because of privacy or other concerns, the user may refuse to provide the input (Liang, Lai, &Ku, 2007). In implicit case (or behavior-based), on the other hand, the system automatically infers the user's preferences passively by monitoring user's behaviors such as analyzing the hyperlinks followed by the customers (Liberman, 1995), the time spent on a particular web page (Kobsa, Koenenmann, &Pohl, 2001; Konstan et al., 1997; Morita &Shinoda, 1994), history of purchases (Krulwich, 1997), or the navigation history. Again, using implicit method to draw preferences still has some disadvantages e.g., sometimes spending more time browsing a page is not equal to having interests in this specific page. Prior studies have proved empirically that the user the implicit method owns the same effect as the explicit method does in taking customers' preferences (Lai, Liang, &Ku, 2003; Zhang &Seo, 2001). Thus, these two methods all have been used to cover their own disadvantages to get customers' preferences.

Recommendation mechanisms can be classified into two types by algorithms and mechanisms used to determine recommended items: (1) collaborative filtering or social filtering, and (2) content-based or attribute-based (Adomavicius &Tuzhilin, 2005; Cosley, Lam, Albert, Konstan, &Riedl, 2003; Liang et al., 2007; Massa &Bhattacharjee, 2004; West et al., 1999). These two mechanisms will be described briefly in the next two sections.

2.1.2 Collaborative filtering Recommendation System

Several collaborative filtering recommendation systems have been developed and applied successfully in enabling the prediction of user preferences in the last two decades (Goldberg et al., 1992; Resnick, Iacovou, Suchak, Bergstrom, &Riedl, 1994; Shardanand &Maes, 1995). Schafer, Frankowski, Herlocker, and Sen (2007) declared that collaborative filtering (or social filtering) is "the process of filtering or evaluating items using the opinion of other people". The major purpose of this mechanism is to aim at finding the relationships among the new user and the existing data to determine the similarity and provide recommendations (Ansari et al., 2000; Balabanovic, 1997; Schafer et al., 2001). For example, if two customers bought similar DVDs and rated these DVDs similarly, the system would recommend to one customer DVDs that the other customer bought and rated positively. Thus, we can say that this system uses "wisdom of the crowd" to recommend items. Figure 2 illustrates how a collaborative filtering recommendation makes the recommendation for a specific user.

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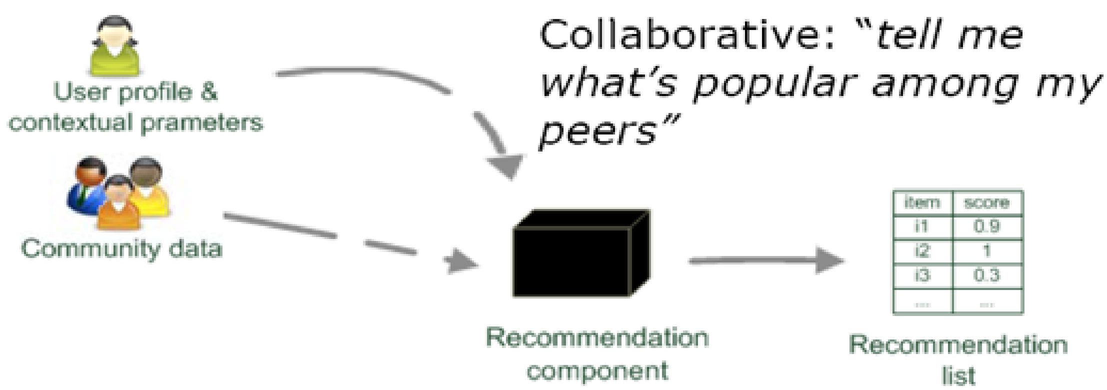


Figure 2. Paradigm of collaborative filtering system, Zanker and Jannach (2010)

In the simplest case, collaborative filtering recommendation 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 (Ansari et al., 2000). In order to make predictions reasonably, the assumption of collaborative filtering is that people with similar preferences will rate things similarly (Schafer et al., 2007). Additionally, Terveen and Hill (2001) mentioned that three essentials are required to build an effective collaborative filtering system: (1) many people must participate (increasing the likelihood that any one person will find other users with similar preferences, (2) the way to represent a user's preferences must be straightforward, and (3) the algorithm must be able to match people with similar preferences.

Generally speaking there are three major processes in this system: (1) object data collections and presentations, (2) similarity decisions and neighborhood creating, and (3) recommendation computation. In the process one, the system can use either implicit or explicit way to collect customers' presences, which are ratings for individual item. In the process two, the system uses different statistical techniques to find a set of customers known as neighbors. These neighbors tend to rate different products similarly or buy similar set of products (Sarwar et al., 2000). In the process three, once the neighbors have been identified, the system uses several algorithms to produce recommendations. As shown in Figure 3, the system makes recommendations to the user based on his current browsing record which is an implicit way to elicit user's preference.

Figure 3. Recommendations from collaborative filtering recommendation system

Due to the limited page, only six recommended cameras are presented here. Normally, the number of recommended items totally depends on how popular of an item the user selected. The more popular item the user selects, the more recommended items will be.

Collaborative filtering algorithms can be divided into memory-based and model-based algorithms (Breese et al., 1998; Sarwar, Karypis, Konstan, &Riedl, 2001). Memory-based algorithm scans the database of preferences or people to locate the peer groups which are "nearest neighbors" for an active user. In terms of identifying the peer group, which is the most important process in collaborative filtering, cosine similarity and correlation are two most popular ways (Adomavicius &Tuzhilin, 2005). In the field of information retrieval field, the similarity between two documents is measured by treating each document as a vector of word frequencies and computing the cosine of the angle formed by these two frequency vectors (Salton &McGill, 1986). In cosine similarity approach, users take the role of documents, titles take the role of the words, and votes take the role of word frequencies (Breese et al., 1998). Using the concept of this, cosine similarity approach calculates the cosine of the angel to find out the similarity between two uses. In correlation approach, Pearson correlation coefficient is used to measure the similarity (Resnick et al., 1994; Shardanand &Maes, 1995). On the other hand, model-based algorithm generates a user model from the database of rating histories first and then makes the recommendations (Sarwar et al., 2001). The building model process is performed by different machine learning algorithm such as neural network, latent semantic indexing (Foltz, 1990), and Bayesian networks (Rich, 1979; Sarwar et al., 2001). Although model-based algorithm requires more time to train, it can provide predictions in a shorter time in comparison to memory-based algorithm.

2.1.2.1 Issues of Collaborative Filtering Recommendation System

There are still some technical issues associated with building an effective collaborative filtering recommendation system. Three major issues are presented as the follow.

(1) Cold-Start problem (Adomavicius &Tuzhilin, 2005; Ansari et al., 2000; Balabanovic &Shoham, 1997; Good et al., 1999): A new item cannot be recommended to users if there is no any rating information about the new item existed in the database. The situation is the same for a new user. A new user cannot receive any recommendation until he provides ratings for some items.

(2) Sparsity (Ansari et al., 2000; Terveen &Hill, 2001): If the number of people who have rated items is relatively small compared to the number of items in the database, it is likely that there is no significant similarity between users. The result is that nearest neighbors cannot be identified very well, thus recommendations will be unreliable. According to Adomanvicius (2005) and Terveen and Hill(2001) , the availability of critical mass of user is the required component for the success of collaborative filtering. Without this

component, many items will be missing to be recommended. For example, in the book section of Amzon.com, there may be many books that have rated positively or bought by few customers and these books would be recommended rarely, even if these books had very high ratings.

(3) Scalability (Sarwar et al., 2000; Schafer et al., 2001): Nearest neighbor algorithms require computation that grow with the number of users and the number of products. With more and more users and products appearing in e-commerce, collaborative filtering recommendation system suffers a serious scalability problem.

2.1.3 Content-based Recommendation System

Content-based (attribute-based) filtering and collaborative filtering have been long viewed as complementary (Adomavicius &Tuzhilin, 2005). Content-based systems analyze item descriptions and user profiles to identity items that users may like (Ansari et al., 2000; Balabanovic &Shoham, 1997; Pazzani &Billsus, 2007). Specifically, this system selects items to recommend based on the correlation between the content of items and users' preferences which are items users have liked in the past as opposed to collaborative filtering that recommends item based on the opinion of others (Meteren &Someren, 2000). Thus, if collaborative filtering recommendation system is a system that locates or recommends "users" that are similar to the user preferences, content-based recommendation system is a system that locates or recommends "items" that are similar to the user preferences. Because content-based system makes the recommendations from only customers' personal preferences, customers may not feel surprising for the results of recommendation. Similar to collaborative filtering system, content-based system also cannot provide recommendations to those who don't specify their preference information. Figure 4 shows the process of making the recommendations in content-based system.

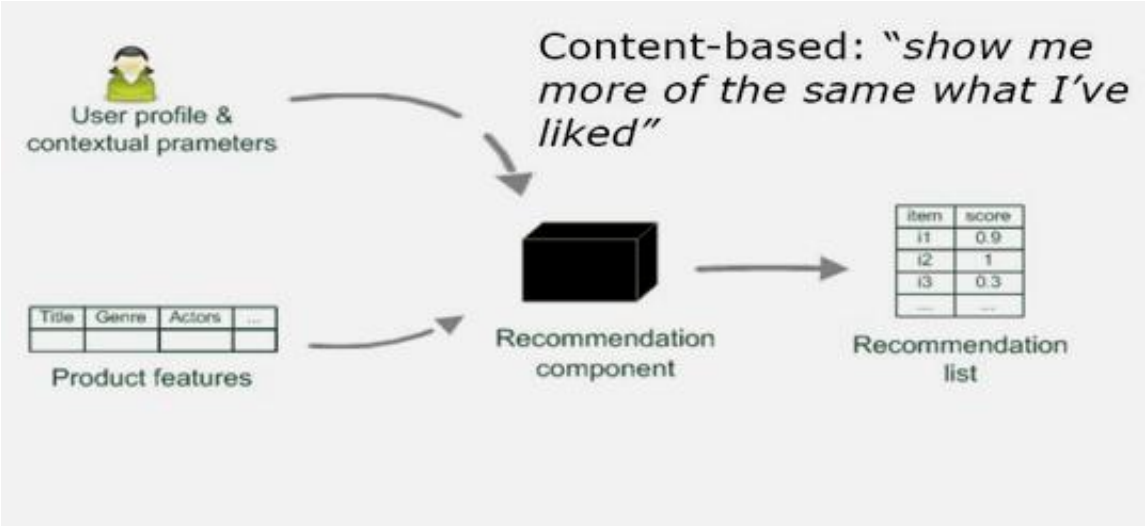


Figure 4. Paradigm of content-based system, Zanker and Jannach (2010)

Content-based uses the assumption that items with similar features will be rated similarly. For example, if you like a digital camera with a large LCD monitor, you may like another camera with a large LCD monitor. Generally, a user dialogue is a common way in content-based system to elicit customers' preferences and needs. As shown in Figure 5, the user answers questions asked by the system for the specific features of camera. The system makes recommendations for every individual based on answers (see Figure 6).

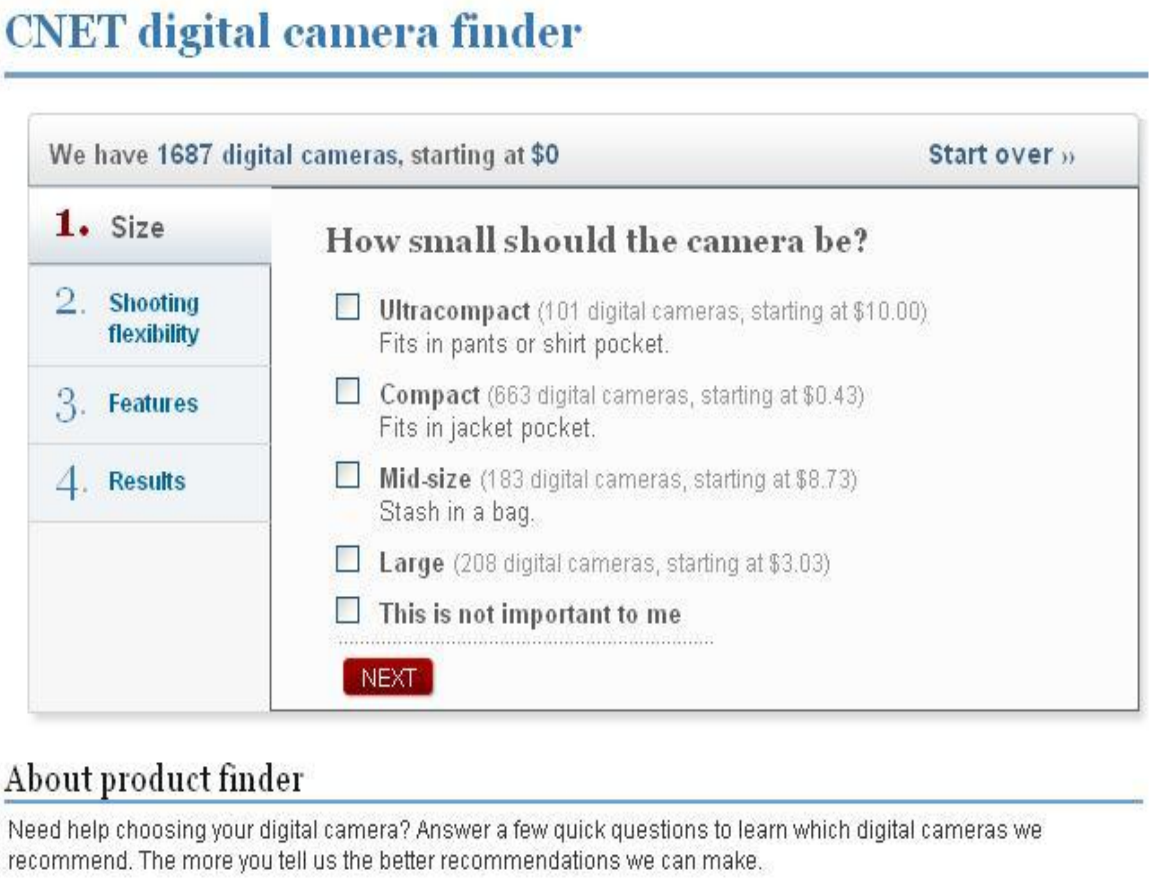


Figure 5. User dialogue from of content-based recommendation system

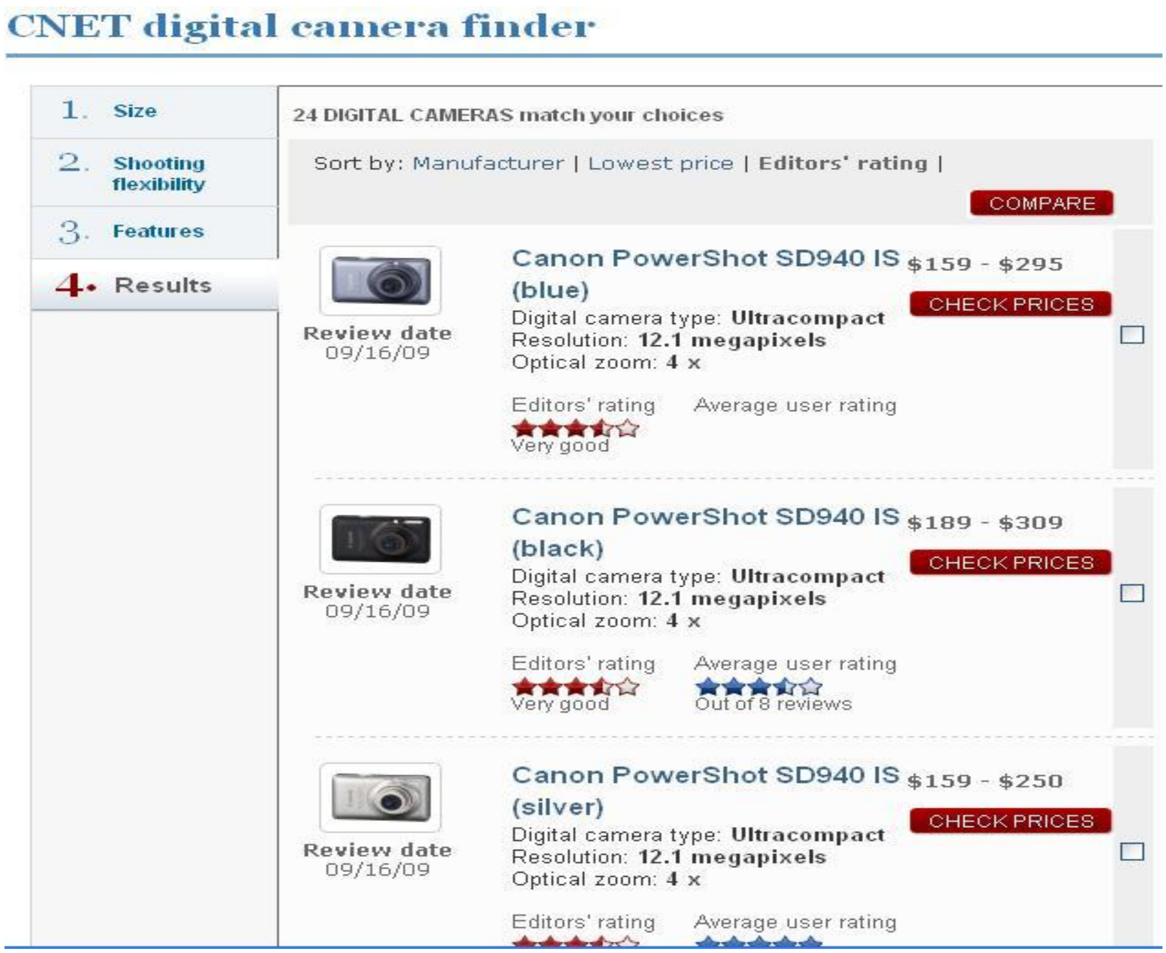


Figure 6. Recommendations from content-based recommendation system

Content-based systems are designed mostly to recommend a text-based item, such as Web sites, or news message (Montaner, López, &Rosa, 2003). In order to recommend these text-based items, keyword or term should be indentified first and will be assigned a specific weight based on its frequency appearing in the whole document (Pazzani &Billsus, 2007). Term-Frequency-Inverse Document Frequency (TF-IDF) (Salton &Buckley, 1988) is a best-known mechanism to specify the weight of the term or keyword. With the information of weighted term, various algorithms can be used to start the matching process and make the recommendation.

Compared to collaborative filtering system which is a user profile matching technology, content-based system is a user profile- item matching technology (Montaner et al., 2003). There are various algorithms used by content-based system to create the recommendation. Few widely used algorithms are presented as follows.

(1) Standard keyword matching: basically, this approach consists of the count of terms which are present in the current description of the new item and in the user profile (Montaner et al., 2003).

(2) Cosine similarity: Using vector space model, this approach is also widely used by collaborative filtering system (Salton &Buckley, 1988). The major difference, however, between collaborative filtering and content-based systems is that in content-based system, cosine similarity approach calculates the cosine of the angel to find out the similarity between item and user profile instead of between two users (Montaner et al., 2003).

(3) Nearest neighbor: This approach computes the distance from the interested item to either the rest of items or the classes of items in user profile.

2.1.3.1 Issues of Content-based Recommendation System

Compared with collaborative filtering, content-based system makes recommendation based on individual user's profile rather than opinions of others. Thus, there is no cold-start or sparsity problems existed in content-based system. However, there are still some shortcomings for content-based system. Few challenges are summarized in the following.

(1) Overspecialization (Adomavicius &Tuzhilin, 2005; Schafer et al., 2007): Content-based systems have no inherent methods for generating serendipitous finds. The system recommends more of what the customer has already seen and indicated a liking for. As a consequence, the user is only restricted to getting the items similar to those have been rated positively.

(2) New user problem (Adomavicius &Tuzhilin, 2005; Pazzani &Billsus, 2007; Schafer et al., 2007): Content-based filtering still has the issue of new user similar to collaborative filtering system. A new user, having few sufficient ratings, cannot get applicable recommendations. However, unlike collaborative filtering, content-based system can provide relevance for items without ratings (e.g., new items).

2.2 Unified Theory of Acceptance and Use of Technology

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. Specifically, TAM provides a fundamental framework to explain and measure the impact of external variables on beliefs, attitudes, and intentions (Davis, 1986; Davis, Bagozzi, &Warshaw, 1989). With the related researches of TAM, researchers have resulted in several theoretical models that routinely explain over 40 percent of variance in individual intention to use technology. Although these different models do have their own effects in explaining individual acceptance case, mostly, researchers need across multiple models to find the favorable constructs or the most applicable model. From researcher's standpoint, this process is a time-consuming job and sometimes ignores the contribution from alternative models (Venkatesh et al., 2003). In order to present a more comprehensive model, Venkatesh et al. (2003) integrated eight related models and proposed the Unified Theory of Acceptance and Use of Technology (UTAUT). In this section, the theoretical fundamentals of these eight models are described briefly.

2.2.1 Underlying Concept of UTAUT

In terms of how and why individuals accept new technologies, two streams have been studied and all contributed a lot in the area of technology acceptance (Venkatesh et al., 2003). One stream focused on individual acceptance of technology by using usage or intention as a dependable variable (Davis, 1986; Davis et al., 1989). Another one concentrated on implementation success at the organizational level and task technology fit. The concept of UTAUT is to aim at using usage as the dependable variable and intention as a predicator of behavior (Venkatesh et al., 2003). Figure 7 shows the fundamental framework of UTAUT.

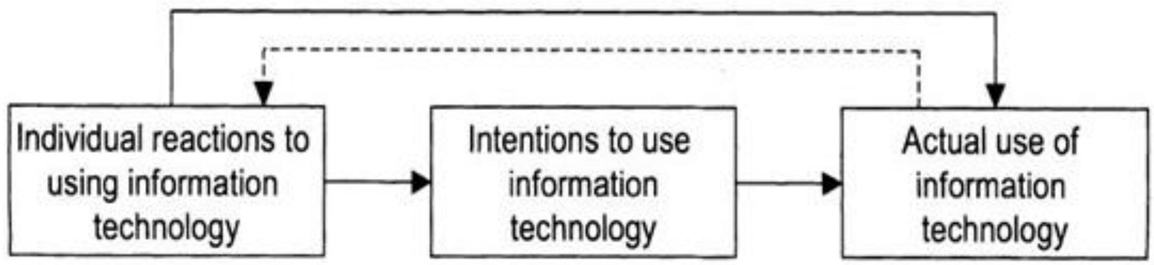


Figure 7. Basic concept of UTAUT, Venkatesh et al. (2003)

Combined with this concept, eight related models in UTAUT are presented as the follow.

1. Theory of Reasoned Action (TRA)
2. Technology Acceptance Model (TAM)
3. Motivational Model (MM)
4. Theory of Planned Behavior (TPB)
5. Combined TAM and TPB (C-TAM-TPB)
6. Model of PC Utilization (MPCU)
7. Innovation Diffusion Theory (IDT)
8. Social Cognitive Theory (SCT)

Generally, the use of information technology is to finish a "job". For example, by using word processor, we can finish the thesis or dissertation in an easy way. In our study, we identify the "job" as the process of shopping in the e-commence. By using the functionality of recommendation systems, people can get more personalized shopping advice to finish the "job" more efficiently and easily. Thus, based on UTAUT, this study attempts to analyze and explain people's motivation beyond using recommendation systems.

2.2.1.1 Theory of Reasoned Action (TRA)

Developed by Ajzen and Fishbein (1980; 1975), TRA was derived from the area of social psychology used to predict and explain the process of making decisions. Attitude, subjective norm, and behavioral intention are three major components of TRA. Attitude is "an individual's positive or negative feelings about performing the target behavior" (Fishbein &Ajzen, 1975). According to Ajzen and Fishbein (1980), people's behavior is determined by behavior intention where behavior intention is influenced by individual's attitude toward the behavior and subjective norm. An individual's positive or negative attitude toward the target behavior will determine the strength of individual's behavior intention. Subjective norm refers to individual's perception of whether people who are important to individual think the performance should be performed. Figure 8 shows the fundamental idea of TRA.

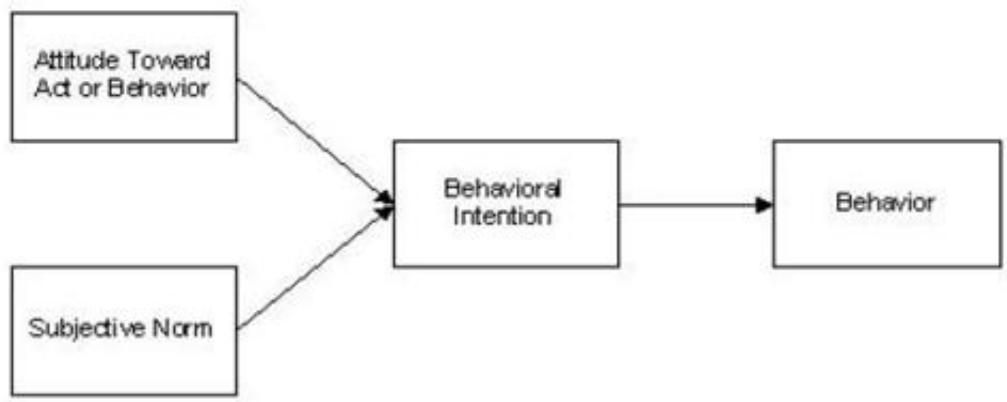


Figure 8. Theory of Reasoned Action (TRA), Ajzen and Fishbein (1980)

2.2.1.2 Technology Acceptance Model (TAM)

Davis (1989) proposed TAM to predict individual's information technology acceptance. As the adaption of TRA, TAM also views that the behavior is determined by behavioral intention. However, attitude toward behavior and subjective norm are replaced by perceived usefulness (PU) and perceived ease of use (PEU). Davis (1989) stated that perceived usefulness (PU) is "the degree to which a person believes that using a particular system would enhance his or her job performance" and perceived ease of use (PEU) is "the degree to which a person believes that using a particular system would be free of effort". TAM has been reexamined and replicated largely and seen as a robust model in the study of technology acceptance (Adams, Nelson, &Todd, 1992; Szajna, 1994; Wixom &Todd, 2005). Figure 9 presents the basic concept of TAM.

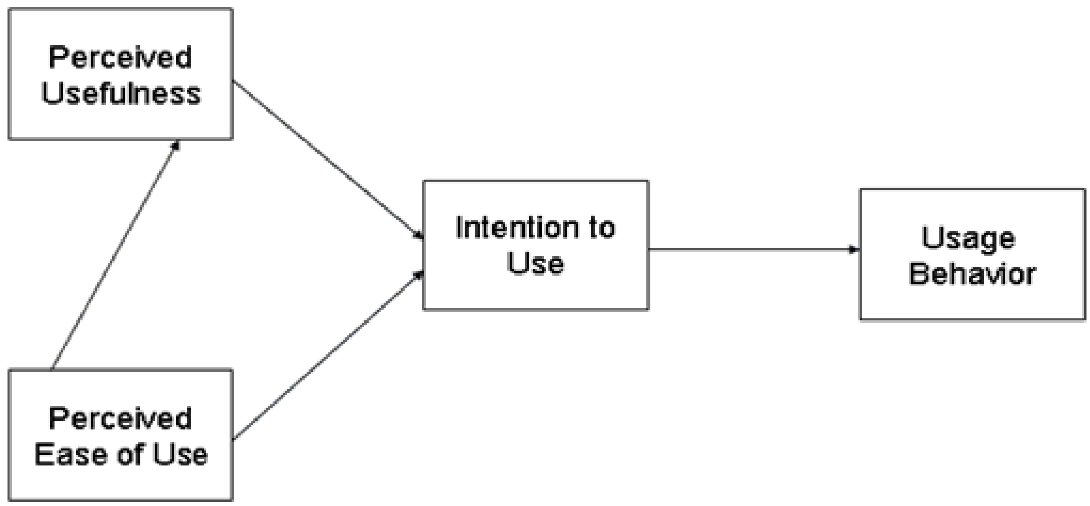


Figure 9. Technology Acceptance Model (TAM), Davis et al. (1989)

2.2.1.3 Motivational Model (MM)

Motivational model assumes that people behave out of two purposes: intrinsic and extrinsic motivation (Davis, Bagozzi, &Warshaw, 1992). Extrinsic motivation is identified as that users will perform an activity because it is perceived to be useful in achieving valued outcomes that are different from the activity itself, such as improved productivity or, salary (Davis et al., 1992). Intrinsic motivation, on the other hand, is identified as that users will perform an activity not from the apparent reinforcement but from the process of performing the activity per se . In the field of psychology, motivational model is applied as an explanation for behavior. In the field of technology acceptance, Davis et al. (1992) used this theory to understand new technology adoption and use.

2.2.1.4 Theory of Planned Behavior (TPB)

Proposed by Ajzen (1992), Theory of Planned Behavior (TPB) is an extension of TRA by adding the construct of perceived behavior control. Perceived behavior control is defined as one's perception of ease or difficulty of performing the behavior or the required resources and opportunities to perform one particular activity (Ajzen, 1992). Applied in the context of IS research, perceived behavior control is the perception of internal and external constraints on behaviors (Taylor &Todd, 1995b). In TPB, individual's behavior is determined by individual's behavioral intention which is the function of attitude toward act or behavior, subjective norm, and perceived behavior control. Figure 10 presents the theoretical basic of TPB.

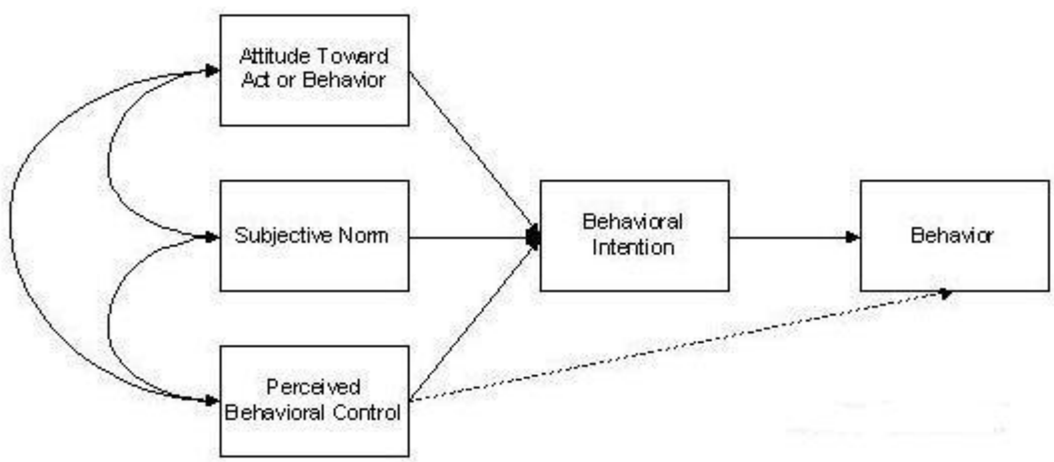


Figure 10. Theory of Planned Behavior (TPB), Ajzen (1992)

2.2.1.5 Combined TAM and TPB (C-TAM-TPB)

Taylor and Todd (1995a) combined constructs of perceived usefulness and perceived ease of use from TAM with constructs of attitude toward behavior, subjective norm, and perceived behavioral from TPB to propose a hybrid model, shown as Figure 11, to explain various cases of technology acceptance. The role of prior experience was added as the moderator to measure it possible effect to influence people's adoption in technology innovation.

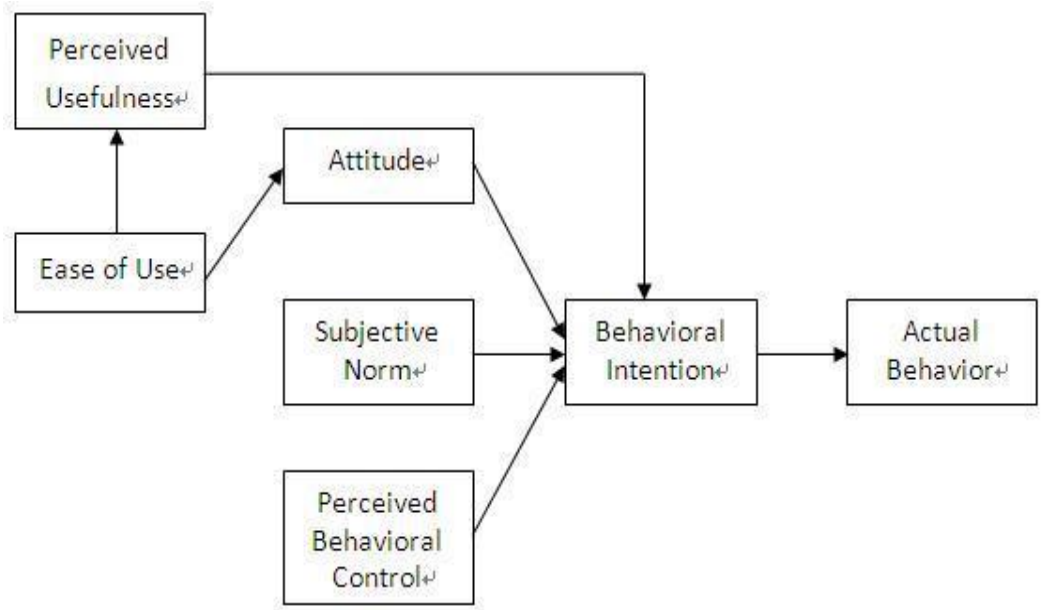


Figure 11. Combined TAM and TPB (C-TAM-TPB), Taylor and Todd (1995a)

2.2.1.6 Model of PC Utilization (MPCU)

Derived from Triandis' (1977) theory of human behavior in the field of psychology, MPCU was refined and adapted by Thompson et al. (1991) for IS contexts to predict PC utilization. Social factors are "the individual's internalization of the reference group's subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations" (Thompson et al., 1991). Affect is positive or negative feeling toward a particular act (Thompson et al., 1991). Facilitating condition is the provision of support that the environment provides in the context of IS. Perceived consequences consist of short-term consequences, which are job-fit, and complexity and long-term consequences, which are outcomes that have a pay-off in the future such as a change in operation schedule that can increase productivity. Basically, job fit is similar to perceived usefulness in TAM, which is the extent that an individual believes that using a technology can enhance the performance of his or her job. Finally, according to Thompson et al. (1991), complexity is the extent to which an innovation is perceived as relatively difficult to understand and use.

2.2.1.7 Innovation Diffusion Theory (IDT)

IDT has been used since the 1960s to study a variety of innovations. In the field of IS, Moore and Benbasat (1991) adapted the characteristics of innovations and proposed a set of constructs and a series of instruments that could be applied to explain and measure individual technology acceptance. Those characteristics of innovation included in Moore and Benbasat' (1991) study are relative advantage, ease of use, image, visibility, compatibility, results demonstrability, and voluntariness of use.

2.2.1.8 Social Cognitive Theory (SCT)

Shown in Figure 12, social cognitive theory (Bandura, 1986) is one of the most powerful theories of human behavior and has been applied extensively and empirically. This theory identifies human behaviors as an interaction of personal factors (e.g., personal motivation, attitude, or thought), environment (e.g., social pressure), and behavior (Bandura, 1986, 1997).

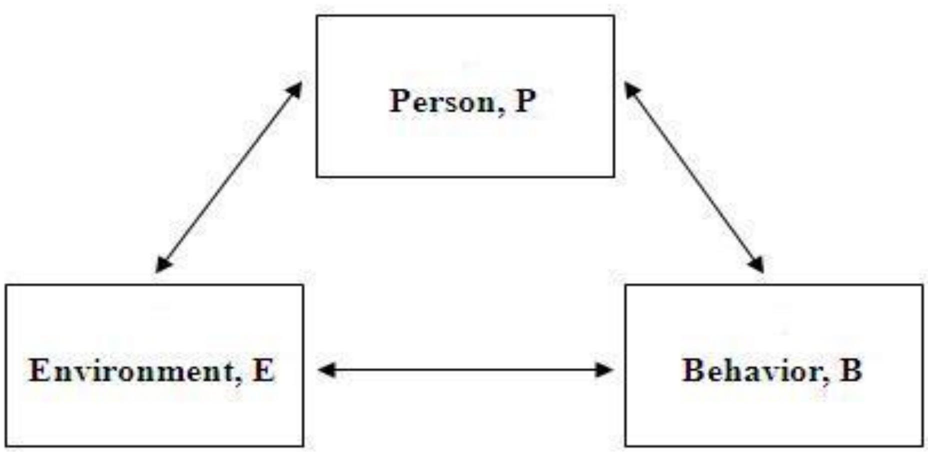


Figure 12. Social Cognitive Theory (SCT), Bandura (1986)

2.2.2 Framework of UTAUT

As presented in figure 13, the UTAUT aims to provide a unified model to explain user intention to use an IS and subsequent usage behavior. Venkatesh et al. (2003) held that four constructs, performance expectancy, effort expectancy, social influence, and facilitating conditions, are major determinants to influence people's behavioral intention and actual behavior in accepting technology. In addition to four major determinants, gender, age, experience, and voluntariness of use are posited to mediate the impact of four major determinants on usage intention and behavior.

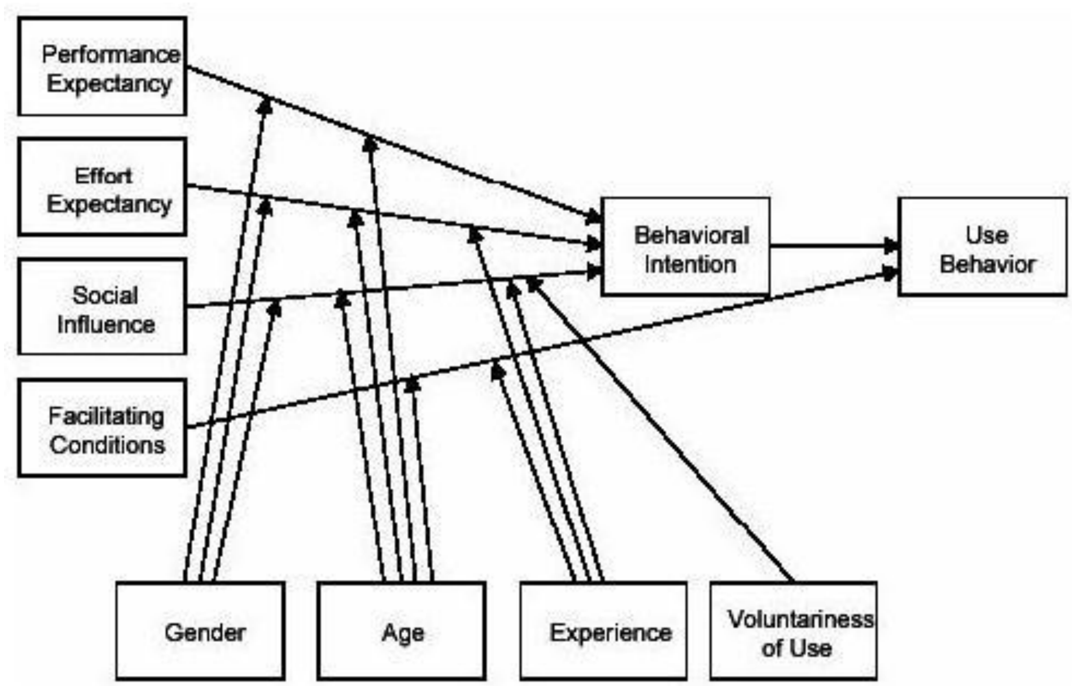


Figure 13. UTAUT model, Venkatesh et al. (2003)

In the next section, four major determinants and four moderators are discussed briefly.

1. Performance Expectancy: Performance expectancy is defined as the degree to which an individual believes that using the system will help him or her to attain gains in job performance (Venkatesh et al., 2003). The five constructs from different models that are associated with performance expectancy are perceived usefulness in TAM/TAM2 and C-TAM/TPB, extrinsic motivation in MM, job-fit in MPCU, relative advantage in IDT, and outcome expectations in SCT. Users of recommendation systems intend to get personalized purchasing advices from the recommended results to finish the job, shopping, effectively. A recommendation system that generates and presents recommendations not concordant with the user's own needs is not likely to improve

decision quality. Thus, our study focuses on whether the recommended results have positive effects on customers in terms of making purchasing decisions and, therefore, influence their intentions to use recommendation systems.

2. Effort Expectancy: Effort expectancy is defined as the degree of ease associated with the use of the system (Venkatesh et al., 2003). The three sub constructs of effort expectancy captured from the existing models are perceived ease of use in TAM/TAM2, complexity in MPCU, and ease of use in IDT. Basically, any type of recommendation system should elicit customers' preferences first and then makes the recommendations based on these preferences. Therefore, the ease for users to generate new or additional recommendations and the amount of control users have when interacting with recommendation systems' preference interfaces influence users' evaluations of recommendation systems. As a consequence, our study seeks to understand whether the degree of the perceived ease of use for a given recommendation system does influence customers' intentions to use the recommendation system.
3. Social Influence: Social influence is defined as the degree to which an individual perceives that important others believe he or she should use the new system (Venkatesh et al., 2003). The associated constructs of social influence captured from previous models are subjective norm in TRA, TAM2, TPB, and C-TAM-TPB, social factors in MPCU, and image in IDT. In our study, social influence is identified as the degree to which the user of a recommendation system perceives that if his/her important peers, friends, or families think he or she should use the recommendation systems.
4. Facilitating Conditions: Facilitating conditions are defined as the degree to which an individual believes that an organization and technical infrastructure exists to support use of the system (Venkatesh et al., 2003). Three major constructs from the previous models define the construct of facilitating conditions: perceived behavioral control from TPB, facilitating conditions from MPCU, and compatibility from IDT. Venkatesh et al. (2003) mentioned that facilitating conditions are moderated by users' experiences and age. In our study, perceived behavioral control is defined as the degree to which an individual perceives that he or she possesses enough knowledge or capacity to use the recommendation system. Facilitating conditions is defined as if any online assistance or

support is available when customers have problems in using the functionalities of recommendation system. For compatibility, this study identifies the use of a recommendation system as a personal behavior that is unnecessary to inconsistent with the existed values of the organization. Thus, the construct of compatibility is not discussed in this study.

5. Moderators: Four moderators, gender, age, experience, and voluntariness of use, are put into UTAUT to take account of every possible situation for accepting technology. Previous research has considered the effects of these moderators and demonstrated their effects in the case of adopting technology. Research indicates that men tend to be highly job-oriented and, therefore, performance expectancies, which concentrate on job accomplishment, are more likely to be noticeable to men (Minton &Schneider, 1980). In addition to gender, age is also considered to play a moderating role. Researches on job-related attitudes shows that younger workers are more responsive to extrinsic rewards (Hall &Mansfield, 1975). In the context of adopting technology, Morris and Venkatesh (2000) held that gender and age differences do influence people's intentions to accept technology. Additionally, Ventatesh et al. (2003) stated that the degree of effort expectancy is moderated by users' age and gender. For example, older females focus more on the effort expectancy of system use. However, with more experience using the system, the effect of effort expectancy will decrease gradually. In the social influence part, women are more sensitive to other's opinions (Miller, 1976; Venkatesh, Morris, &Ackerman, 2000). Thus, social influence is likely to be more salient to women when forming an intention to use technology. Furthermore, facilitating condition is also moderated by age and experience. Prior research shows that supportive help or assistance grabs more older workers' attention (Hall &Mansfield, 1975).

2.3 Trust

Customers often hesitate to interact with Web-based vendors because of uncertainty of performance engaged in by these vendors or the perceived risk of personal information stolen by hackers (McKnight, Choudhury, &Kacmar, 2002). Human beings tend to reduce their social uncertainty, that is, they seek ways to understand, predict, and occasionally attempt to control the behavior of other people (Gefen &Straub, 2004). However, the impossibilities of controlling actions of others or understanding others' thoughts or motivations make the situation so complicated that it reduces people's intentions to perform a particular action. When people cannot reduce social uncertainty through rules or customs, they resort to trust, one of the most effective methods to reduce social uncertainty and complexity, as a major method to reduce social uncertainty (Kelley, 1979; Luhmann, 1979; Thibaut &Kelley, 1978). As a consequence, in the context of high social uncertainty, such as e-commerce, trust plays a central role in reducing social uncertainty and helping customers overcome the perceived risk of exposing personal information.

What is trust? A variety of definitions of trust are given by different disciplines. Broadly, trust is the belief that other people will respond in an predictable way (Luhmann, 1979). In the discipline of management and marketing, trust is "a willingness to rely on an exchange partner in whom one has confidence and is dependent on developing shared values and effective communication" (Moorman, Deshpande, &Zaitnnan, 1993). Similarly, Geyskens et al. (1996) defined trust as that people believe or expect that vendor's promise or behavior can be relied on and the vendors will not take advantage of the customers' vulnerabilities. In the discipline of psychology, trust is defined as a tendency to trust others (Rotter, 1971). In the discipline of social psychology, trust is defined as a cognition about the trustee (Rempel, Holmes, &Zanna, 1985).

Previous research focused more on applying the concept of trust into the acceptance of e-commerce, showing that trust does influence people's intentions for shopping in the realm of e-commerce (Gefen, 2000; Gefen, Karahanna, &Straub, 2003b; Gefen &Straub, 2003). The major reason behind this is that the buyers should trust first that e-vendors will not take advantages of using their personal information (i.e., credit number) illegally or inappropriately and then shop in the context of e-commerce. In other words, privacy concern, which is the consequence of revealing personal information, is the top priority for customers when transacting with e-vendors. The same situation can be applied in the setting of recommendation systems. In order to get the most personalized recommendations, users should express preferences or personal information more clearly. The clearer preferences or personal information users express the more accurate and personalized recommendations users will get. However, with providing more and clearer preferences, users are concerned more about the risk of unwanted exposure of personal information (Lam, Frankowski, &Riedl, 2006). Therefore, in order to initiate the whole process of generating the recommendations, the users of recommendation system should trust the providers of recommendation system first that they will not abuse their personal information. In addition to the input part of the whole process, the users also need to trust the output of the whole process, the recommended recommendations. If the users don't trust the recommended recommendations, they will not intend to use the recommendation system. Thus, the definition of trust in this study is that the providers of a recommendation system will respond to people's needs, getting the most personalized recommendations, in a predictable way.

2.4 Types of Products

Previous research has demonstrated that hedonic and utilitarian products have different effects on customer behaviors and attitudes (Heijden, 2004; Hirschman &Holbrook, 1982; King &Balasubramanian, 1994). Hedonic products provide more experiential consumption, pleasure, fantasy, fun, and excitement, whereas utilitarian products are instrumental, functional, and goal oriented (Dhar &Wertenbroch, 2000; Hirschman &Holbrook, 1982). Additionally, Goetzinger and Park mentioned (2005) that hedonic products are typically discretionary and utilitarian products are typically necessary.

2.5 Research Model

Based on the discussions above, the research model of this study is schematized in Figure 14. The major differences between this study and the original UTAUT study lies in the temporal dimension and changes of external variables to fit the current study. For the temporal dimension, Venkatesh et al. (2003) measured people's actual usage behavior in three time spans. Contrasted to the original UTAUT study, this study only focuses on one time span to measure people's intentions to use the recommendation system. For external variables, this study only focuses on measuring people's intentions to accept two types of recommendation systems rather than measuring people's actual behavior of using the recommendation system. As a consequence, the construct of facilitating condition, which only influences people's actual usage behavior, is removed from the original model. The construct of trust, an important concept in e-commerce, is added to the research model to measure people's intentions. Venkatesh et al. (2003) stated that people's degree of familiarity with the system will be changed with time. This difference of familiarity can be used to measure the effect of experience in every construct. But this study only focuses on snapshot of use of the recommendation system. Therefore, the original form of experience is not appropriate in this study. The moderator of experience in this study is identified as an individual's habit of using recommendation system in the past (Venkatesh &Davis, 1996). The major target of this study concentrates on ISU Business undergraduate students. Most of them are younger age average. Thus, the moderator of age is removed from the original model. For the moderator of voluntariness of use, the use of the recommendation system in this study is identified as the personal use of getting purchasing advice. No difference in voluntariness use can be considered in this study. Thus, the moderator of voluntariness use is removed from the original model. Additionally, because utilitarian and hedonic products have different effects to influence people's attitudes and behaviors (Heijden, 2004; Hirschman &Holbrook, 1982), these two types of products are used as a moderator to measure people's intentions.

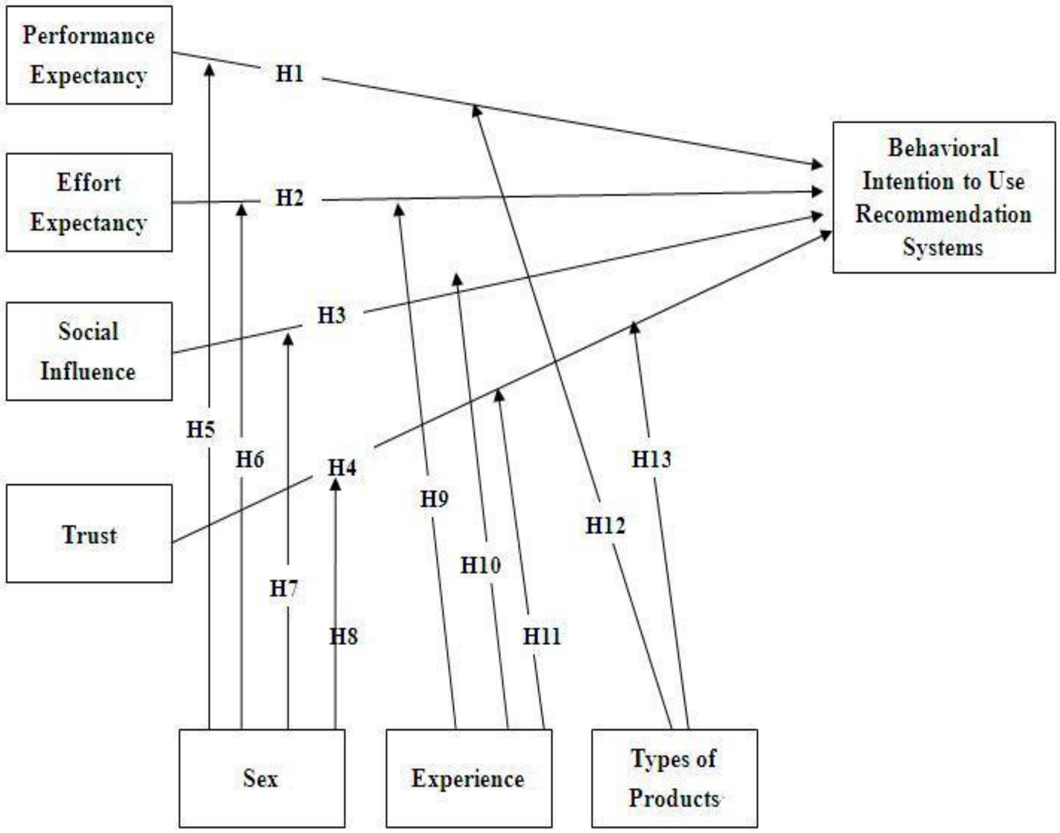


Figure 14. Proposed research model

2.6 Research Hypotheses

Previous studies show that performance expectancy is the strongest predicator of intention in accepting or rejecting a technology (Davis, 1989; Davis et al., 1989; Moore &Benbasat, 1991; Venkatesh &Davis, 2000). Therefore, Hypothesis 1 can be proposed as:

H1. Performance expectancy will have a positive effect on intention to use the recommendation system.

Similar to performance expectancy, effort expectancy has been shown to positively influence people to accept or reject a technology. A technology perceived to be easier to use than another is more likely to be accepted by the user (Davis, 1989). Thus, Hypothesis 2 can be stated in a similar way.

H2. Effort expectancy will have a positive effect on intention to use the recommendation system.

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 &Benbasat, 1991; Taylor &Todd, 1995b; Thompson et al., 1991; Venkatesh &Davis, 2000). As a result, Hypothesis 3 can be proposed as:

H3. Social influence will have a positive effect on intention to use the recommendation system.

Trust has been empirically validated as one of the most important determinants to purchase intention by online shoppers (Gefen, 2000; Gefen, Karahanna, &Straub, 2003a; Gefen et al., 2003b; Gefen &Straub, 2003; Reichheld &Schefter, 2000). Customers' trust in an e-vendor can reduce their concerns in the risk of exposing privacy issue such as credit card information or uncertainty when shopping on line (Gefen et al., 2003a, 2003b). The same situation can be applied in the context of recommendation systems. In order to provide the most customized recommendation to the user, recommendation agents involved in inquiring customer's personal information or preferences first to generate the recommendation. Thus, if the users don't have enough trust in a recommendation agent, they are not likely to use it or may switch to another recommendation agent (Koufaris, 2002). To summarize, Hypothesis 4 can be summarized as:

H4. Trust in the recommendation system will have a positive effect on intention to use the recommendation system.

Research on sex difference indicates that men tend to be likely task-oriented (Minton &Schneider, 1980). As a result, performance expectancy, which focuses on task accomplishment, is salient to men (Venkatesh et al., 2003). Therefore, Hypothesis 5 can be stated as:

H5. The effect of performance expectancy on intention to use the recommendation system will be moderated by the sex of the user.

Previous studies have shown that effort expectancy is more salient to women than men (Venkatesh &Morris, 2000; Venkatesh et al., 2000). Thus, Hypothesis 6 can be proposed as:

H6. The effect of effort expectancy on intention to use the recommendation system will be moderated by the sex of the user.

Theory suggests that women tend to be more sensitive to other's opinions (Miller, 1976; Venkatesh et al., 2000). Therefore, Ventatesh et al. (2003) stated that the effect of social influence will be more salient to women than men when forming the intentions to accept a new technology. Thus, Hypothesis 7 can be proposed as:

H7. The effect of social influence on intention to use the recommendation system will be moderated by the sex of the user.

Research has demonstrated that female customers have more trust concerns than men and are less likely to purchase on line (Chaudhuri &Gangadharan, 2002; Sheehan, 1999). Therefore, Hypothesis 8 can be presented as:

H8. The effect of trust on intention to use the recommendation system will be moderated by the sex of the user.

The effect of effort expectancy is significant during the first time period of accepting the technology; however, it becomes nonsignificant over an extended period and sustained usage (Davis et al., 1989; Thompson et al., 1991; Venkatesh et al., 2003). Thus, Hypothesis 9 can be proposed as:

H9. The effect of effort expectancy on intention to use the recommendation system will be moderated by experience.

The relative influence of social influence on intentions is expected to be stronger to those who don't have prior experiences because they rely on other's reactions to form their intentions (Burnkrant &Cousineau, 1975; Davis et al., 1989; Thompson et al., 1991;

Venkatesh et al., 2003). However, the influence of social influence will be attenuated over time as people have more experiences in one specific event (Venkatesh et al., 2003). Thus, Hypothesis 10 can be stated as:

H10. The effect of social influence on intention to use the recommendation system will be moderated by experience.

The effect of trust changes over time with experiences (Gefen et al., 2003a). Trust is particularly important for those who interact with recommendation agents for the first time and have a limited understanding of agents' behaviors (Wang, W. &Benbasat, 2005). They should trust the recommendation agent first for not taking advantage of their vulnerabilities. Otherwise, they are likely to shift to another recommendation agent or not to use it. Therefore, Hypothesis 11 can be presented as:

H11. The effect of trust on intention to use the recommendation system will be moderated by experience.

Hedonic and utilitarian products have different effects on customer purchasing perceptions (Heijden, 2004; Hirschman &Holbrook, 1982). Hirschman and Holbrook (1982) described customers as either a "problem solver" or seekers of "fun, fantasy, arousal, sensory stimulation, and enjoyment." Therefore, performance expectancy, which focuses on task accomplishment, will be different based on the products customers want to purchase. More specifically, the meaning of task accomplishment for those who buy a hedonic product is likely to seek fun, arousal, and enjoyment. On the other hand, the meaning of task accomplishment for those who buy utilitarian product is more likely to focus on task-oriented or instrumental needs. Thus, Hypothesis 12 can be proposed as:

H12. The effect of performance expectancy on intention to use the recommendation system will be moderated by product types.

Research in advertising suggests that the influence of an endorser or spokesperson is likely to be judged on whether the product is viewed as hedonic or utilitarian purchase (Feick &Higie, 1992; Stafford, Stafford, &Day, 2002). In utilitarian purchase situation, customers consider more on the functional attributes of items (Heijden, 2004; Hirschman &Holbrook, 1982). In this situation, customers have found to prefer endorses who are experts or at least experiences with this utilitarian product to help them evaluate the functional attributes of this product (Feick &Higie, 1992; Stafford et al., 2002). In other words, customers who make utilitarian purchases will trust experts or at least experiences with this utilitarian product more to evaluate or provide some advice for this product. The recommendation system is viewed as an online expert with experiences dealing with a specific product. Thus, Hypothesis 13 can be presented as:

H13. The effect of trust on intention to use the recommendation system will be moderated by product types.

2.7 Definitions of Variables

The constructs examined in this study are performance expectancy, effort expectancy, social influence, trust, gender, experience, and types of products. The definitions of these variables are identified in the following section.

2.7.1 Performance Expectancy

Performance expectancy for the recommendation system is defined as the degree to which an individual believes that using the recommendation 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) (Venkatesh et al., 2003).

2.7.2 Effort Expectancy

Effort expectancy for the recommendation 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)

2.7.3 Social Influence

Social influence for the recommendation system 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.

2.7.4 Trust

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

2.7.5 Behavioral Intentions to Use Recommendation Systems

Based on Theory of Planned Behavior (Fishbein &Ajzen, 1975), behavioral intentions to use recommendation systems is defined as a person's readiness to use the recommendation system to receive purchasing advices.

2.7.6 Sex

Venkatesh et al. (2003) mentioned that gender difference results in the difference of performance expectancy, effort expectancy, and social influence of accepting a technology. Additionally, previous research shows that men exhibit greater of trust than women do (Chaudhuri &Gangadharan, 2002; Sheehan, 1999). Thus, gender is used as moderator to measure potential difference of influencing people's intentions to accept the recommendation system.

2.7.7 Experience

Prior experience of using a technology has been demonstrated to influence performance expectancy, effort expectancy, social influence, and trust of accepting a new technology (Gefen et al., 2003a; Venkatesh et al., 2003). Experience is defined as participant's previous experiences, knowledge, and familiarity with using the recommendation system.

2.7.8 Types of Products

A hedonic product is defined as a product that can provide more experiential consumption, pleasure, fantasy, fun, and excitement, whereas utilitarian product is instrumental, functional, and goal oriented (Dhar &Wertenbroch, 2000; Hirschman &Holbrook, 1982). Further details about the selected hedonic and utilitarian product will be provided in the Methodology and Procedures and Result section.

CHAPTER 3. METHODOLOGY AND PROCEDURES

3.1 Pilot Test

3.1.1 Participants

For the product manipulation study, 27 participants were recruited from the undergraduate course in Management Information Systems at a major Midwestern university. These students were offered extra credit in the class they were recruited from for participation in a study.

3.1.2 Procedure

An online survey was conducted to select the most diverse pair of items. Participants were asked to evaluate a set of product classes: cell phones, laptop computers, desktop computers, digital cameras, MP3 players, TVs, camcorders, printers, and GPSs. For each product class, subjects were asked whether products could be considered to be closer to being utilitarian or hedonic, exciting or dull, pleasant or unpleasant, and interesting or boring (see Appendix B for the manipulation study). According to results, MP3 players represented the most hedonic product class, and printers represented the most utilitarian. These two product types were used to examine their effects on customer usage of two types of recommendation systems. Please see the Results section for further details.

3.2 Final Study

A quasi experimental crossover design was conducted. Subjects were requested to navigate and go through two types of recommendation systems before filling in the experimental instrument. An online survey was conducted to identify factors that support or impede the acceptance of online recommendation systems in e-commerce. Shopping.com (http://www3.shopping.com/) was the research context of collaborative filtering recommendation system and CNET Reviews (http://reviews.cnet.com/) was the research context of content-based recommendation system. The MP3 player was the hedonic product and the printer was the utilitarian one to measure potential differences of adopting two types of recommendation systems.

3.2.1 Participants

The sample for this research consisted of 51 undergraduate students from the undergraduate course in Marketing at a major Midwestern university. Please see the Results section for detailed demographic information. Participation was voluntary and students were rewarded extra credit for the course for taking part in the study. They were instructed to sign-up for a time when they could go to a lab-type room. During the period of the study, they were asked to individually engage in a series of tasks aimed at getting purchasing advice, and then respond to survey questions. A web survey tool was used to present the material, and then administer the measures.

3.2.2 Procedure

Stimuli presentation and questionnaire completion took place in a teaching laboratory commonly used for a variety of computer-based business classes. There were three experimental sessions, with a maximum number of 20 participants per session. Total laboratory time was one hour. At the beginning of each session, students were asked to sit quietly with their PC monitors turned off. They were told that a session leader would guide them by illustrating two types of recommendation systems with the help of images projected on a screen in the front of the room. In an attempt to prevent the primary recency effect (Anderson, N. H. &Barrios, 1961), the order of illustration was completely randomized. The presentation was divided into two parts. In the first part, the session leader gave participants brief background about the purpose of the study and definitions of two types of recommendation systems. After the first part of presentation, participants were asked to respond with their personal information, pre self-efficacy of online recommendations, and previous online experiences and future intentions of purchasing MP3 player and printers online.

The session leader continued to the second part of presentation once all participants finished the first part of survey. In the second part of the presentation, the session leader gave participants clearer explanations of two types of recommendation systems and illustrated these two online recommendation systems. Participants were encouraged to ask questions about online recommendation systems as the initial demonstration proceeded. The purpose was to orient and provide participants a baseline of familiarity across subjects related to the basic capabilities of getting purchasing advice from two types of recommendation systems.

At the end of the 15 min pre-exposure demonstration, the session leader instructed participants to access the second part of the survey. All participants were asked to navigate to the Shopping.com and CNET Reviews to get personalized recommendations of MP3 player and printer. Participants were requested to finish four tasks and respond to survey questions regarding every individual task they just experienced respectively. The order of four tasks was randomized to prevent the learning effect. The purpose of four tasks was to ensure that subjects have enough real experiences of getting product recommendations. The instrument of these four tasks was provided at the first beginning of each survey page. Subjects could follow this instrument step by step to finish the task.

3.3 Measure

This study used existing validated scales. In the product manipulation study, the measure of perceived enjoyment was adapted from van der Heijden (2004). The original first item, enjoyment-disgusting, was used to measure the characteristics of hedonic information systems. But this study is to measure the characteristics of product. Thus, the original first item was replaced by hedonic - utilitarian to fit the content of this study. All items were set in seven point semantic differentials. See Appendix A for the product manipulation pilot study.

For the first part of the final survey, participants provided self-reported sex (choice of “Male” or “Female”), age (choice of “Under 19 years”, “20~25 years”, “26~30 years”, “31~35 years”, “35~40 years”, or “Over 40 years”), U.S. citizens (choice of “Yes” or “No”), ethnicity (choice of “Hispanic or Latino”, “American Indian/Alaskan Native”, “Asian”, “Black or African American”, “Native Hawaiian or Other Pacific Islander”, “White”, or “Other”), previous experiences of purchasing printers and MP3 player online (seven-point Likert scale, ranging from strongly disagree to strongly agree), the intent to buy printers and MP3 players online in the future (seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7)), the list of brand of printer participants bought online before, the list of brand of printer participants may like or buy online in the future, the list of brand of MP3 player participants bought online before, the list of brand of MP3 player participants may like or buy online in the future. In addition to self-reported questionnaires, the survey instrument contains the computer self-efficacy, in conformance with the computer self-efficacy instrument developed by Marakas et al. (2007), to measure participants' computer self-efficacy of using recommendation systems. Computer self-efficacy refers to an individual's perception of efficacy in performing specific computer-related tasks and judgment of capability to use a computer (Compeau &Higgins, 1995; Marakas, Yi, &Johnson, 1998). The measure of computer self-efficacy (seven-point Likert scale, ranging from strongly disagree to strongly agree) in this study was designed by researchers who are familiar with the computer self-efficacy and online recommendation systems. Computer self-efficacy was measured in two stages: pre computer self-efficacy was measured after the first part of presentation and the computer self-efficacy was measured after the second part of presentation.

For the second part of the final survey, participants provided self-reported use of recommendation systems (four point semantic differentials, ranging from never use (1) to often use (4)). In addition the self-reported use of recommendation systems, measurement of PE, EE, SI, and BI were adapted from Venkatesh et al.'s (2003) UTAUT scales. The original UTAUT model was conducted to measure the technology acceptance in the organization or company. In the UTAUT model, SI-3 and SI-4 were performed to measure the reaction of senior managers and the business in supporting the use of technology. Thus, SI-3 and SI-4 were removed and two new items were added in to fit the research content of this study. Validated measures for familiarity and trust were adopted from Gefen (2000), who assessed the importance of trust on book purchase at Amazon.com, and modified to suit the research context. Familiarity refers to familiarity with two types of recommendation systems and uses to probe subject's past experiences or habits of using these two types of recommendation systems. The measure of computer self-efficacy, in conformance with the computer self-efficacy instrument developed by Marakas et al. (2007), was designed by researchers who are familiar with the computer self-efficacy and online recommendation systems. All items were assessed on a 7 point scale ranging from Strongly Disagree (1) to Strongly Agree (7).

See Appendix B for the final study.

CHAPTER 4. RESULTS

4.1 Pilot Test

In order to select the most appropriate hedonic and utilitarian product in the final study, a pilot test was conducted first. The major purpose of this test was only used to select the most diverse pair of items to use in the final study. There were 27 participants in the product manipulation study. The analysis used the SPSS statistical software package. The descriptive statistics of product manipulation is shown in Table 2.

Table 2. Descriptive statistics of the product manipulation study

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Cell_phone	27	1.25	5.50	2.6574	1.02879
Laptop	26	1.00	6.00	2.5577	1.00824
Digital_Camera	27	1.00	6.75	2.8333	1.44947
Desktop	26	1.00	7.00	3.1538	1.36579
MP3	27	1.00	4.75	2.1667	.96825
TV	26	1.00	5.25	2.5673	1.13921
Camcoder	24	1.75	6.50	3.3646	1.28321
Printer	27	2.00	6.75	5.0556	1.33613
GPS	27	1.00	6.50	3.6852	1.36507
Valid N (listwise)	21				

Results of the product manipulation indicated that the MP3 player product class was the most "hedonic" product (mean=2.1667) and the printer product class was the most "utilitarian" product (mean=5.0556). Furthermore, the difference between the results of the MP3 player and the printer was significant. The paired sample T Test was conducted to compare the means of these two product classes. The comparison of the means of MP3 player and printer is shown in Table 3.

Table 3. Comparison of the means of MP3 player and printer

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	MP3 - Printer	-2.88889	1.67466	.32229	-3.55136	-2.22642	-8.964	26	.000

4.2 Final Study

In the final study, SPSS was first used for descriptive statistics and profiled the characteristics of sample data. Partial least squares (Visual PLS, Version 1.04) was used to examine the reliability and validity of the measures and models. Specifically, 5 separate validity tests (4 treatments and a pool of four treatments) were run to examine convergent and discriminant validity. Finally, PLS was performed to test measurement models of five cases separately and hypotheses that we assumed before.

4.2.1 Data Characteristics

4.2.1.1 Demographic Information

Data was gathered through 51 undergraduate students enrolled in Marketing course at a major Midwestern university. 52.9% of the respondents were male (N=27) and 47.1% were female (N=24). 9.8 % of the respondents were less than 19 years of age (N=5), 88.2% were 20 to 25 (N=45), 2% were 26 to 30 (N=1). 71% of participants were US citizens (N=36). Approximately 64.7 % of the participants were White, and the remaining participants were relatively across Asians (29.4%), Hispanics or Latinos (3.9%), and Blacks (2%). The Demographic information of 51 samples is shown in Tables 4, 5, 6, and 7.

Table 4. Sex information

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	27	52.9	52.9	52.9
	Female	24	47.1	47.1	100.0
	Total	51	100.0	100.0	

Table 5. Age information

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Under 19 years	5	9.8	9.8	9.8
	20~25 years	45	88.2	88.2	98.0
	26~30 years	1	2.0	2.0	100.0
	Total	51	100.0	100.0	

Table 6. US citizen information

US_citizen

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	36	70.6	70.6	70.6
	No	15	29.4	29.4	100.0
	Total	51	100.0	100.0	

Table 7. Ethnicity information

Ethnicity

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Hispanic or Latino	2	3.9	3.9	3.9
	Asian	15	29.4	29.4	33.3
	Black or African American	1	2.0	2.0	35.3
	White	33	64.7	64.7	100.0
	Total	51	100.0	100.0	

Approximately 75% of the participants did not have previous experience purchasing printers online and around 53% of the participants did not have previous experience purchasing MP3 player online. In addition, more than 52% of the participants will not plan to buy the printer online and approximately 41% of all participants will not plan to buy a MP3 player online. The past experience of purchasing printers and MP3 player online is shown in Tables 8 and 9. The future intent of purchasing printers and MP3 players online is shown in Tables 10 and 11.

Table 8. Past experiences of purchasing printers online

Print_experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree	15	29.4	29.4	29.4
	Disagree	16	31.4	31.4	60.8
	Somewhat Disagree	6	11.8	11.8	72.5
	Neither Agree nor Disagree	1	2.0	2.0	74.5
	Somewhat Agree	3	5.9	5.9	80.4
	Agree	8	15.7	15.7	96.1
	Strongly Agree	2	3.9	3.9	100.0
	Total	51	100.0	100.0	

Table 9. Past experiences of purchasing MP3 players online

MP3_experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree	9	17.6	17.6	17.6
	Disagree	10	19.6	19.6	37.3
	Somewhat Disagree	4	7.8	7.8	45.1
	Somewhat Agree	4	7.8	7.8	52.9
	Agree	12	23.5	23.5	76.5
	Strongly Agree	12	23.5	23.5	100.0
	Total	51	100.0	100.0	

Table 10. Future intent of purchasing printers online

Pri_intent

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree	8	15.7	15.7	15.7
	Disagree	16	31.4	31.4	47.1
	Somewhat Disagree	3	5.9	5.9	52.9
	Neither Agree nor Disagree	14	27.5	27.5	80.4
	Somewhat Agree	6	11.8	11.8	92.2
	Agree	4	7.8	7.8	100.0
	Total	51	100.0	100.0	

Table 11. Future intent of purchasing MP3 players online

MP3_intent

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree	5	9.8	9.8	9.8
	Disagree	12	23.5	23.5	33.3
	Somewhat Disagree	4	7.8	7.8	41.2
	Neither Agree nor Disagree	13	25.5	25.5	66.7
	Somewhat Agree	8	15.7	15.7	82.4
	Agree	8	15.7	15.7	98.0
	Strongly Agree	1	2.0	2.0	100.0
	Total	51	100.0	100.0	

For the pre self-efficacy test, most of participants showed a high degree of self-efficacy on the recommendation system. Table 12 presents descriptive statistics of the pre self-efficacy.

Table 12. Descriptive statistics of pre self-efficacy

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
SE1_pre	51	3	7	5.78	.832
SE2_pre	51	3	7	5.78	.856
SE3_pre	51	3	7	5.75	.891
SE4_pre	51	2	7	5.73	.961
Valid N (listwise)	51				

4.2.1.2 Past Experiences of Using Recommendation Systems

All subjects were asked to respond about their past experiences and familiarity regarding getting product advices from four treatment levels. The test of self-efficacy was also asked again after the first part of presentation to measure potential differences between the pre self-efficacy and the self-efficacy of using recommendation systems. This part of information was conducted to measure the moderating influences of experience. Tables 13, 14, and 15 present information about past experiences, familiarity, and self-efficacy of using the recommendation system in the case of treatment 1: getting MP3 player purchase advices from collaborative filtering recommendation system.

Table 13. Past experiences for the treatment 1

Past experiences in the treatment 1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never Use	2	3.9	3.9	3.9
	Rarely Use	15	29.4	29.4	33.3
	Sometimes Use	27	52.9	52.9	86.3
	Often Use	7	13.7	13.7	100.0
	Total	51	100.0	100.0	

Table 14. Familiarity for the treatment 1

Descriptive Statistics

	N	Minimum		Mean	Std. Deviation
Familiarity1_1	51	1	7	5.59	1.080
Familiarity2_1	51	2	7	5.67	.931
Valid N (listwise)	51				

Table 15. Self-efficacy information in the treatment 1

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
SE1_1	51	3	7	5.84	.758
SE2_1	51	3	7	5.59	.983
SE3_1	51	4	7	5.78	.783
SE4_1	51	4	7	5.84	.731
Valid N (listwise)	51				

Tables 16, 17, and 18 present information about past experiences, familiarity, and self-efficacy of using the recommendation system in the case of treatment 2: getting printer purchase advices from collaborative filtering recommendation system.

Table 16. Past experiences for the treatment 2

Past experiences in the treatment 2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never Use	5	9.8	9.8	9.8
	Rarely Use	15	29.4	29.4	39.2
	Sometimes Use	24	47.1	47.1	86.3
	Often Use	7	13.7	13.7	100.0
	Total	51	100.0	100.0	

Table 17. Familiarity for the treatment 2

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Familiarity1_2	51	2	7	5.55	1.154
Familiarity2_2	51	2	7	5.59	.942
Valid N (listwise)	51				

Table 18. Self-efficacy for the treatment 2

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
SE1_2	51	3	7	5.86	.849
SE2_2	51	3	7	5.76	.885
SE3_2	51	3	7	5.75	.771
SE4_2	51	3	7	5.76	.790
Valid N (listwise)	51				

Tables 19, 20, and 21 present information about past experiences, familiarity, and self-efficacy of using the recommendation system in the case of treatment 3: getting MP3 player purchase advices from content-based recommendation system.

Table 19. Past experiences for the treatment 3

Past expericnes in the treatment 3

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never Use	6	11.8	11.8	11.8
	Rarely Use	18	35.3	35.3	47.1
	Sometimes Use	20	39.2	39.2	86.3
	Often Use	7	13.7	13.7	100.0
	Total	51	100.0	100.0	

Table 20. Familiarity for the treatment 3

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Familiarity1_3	51	1	7	5.10	1.526
Familiarity2_3	51	2	7	5.25	1.369
Valid N (listwise)	51				

Table 21. Self-efficacy for the treatment 3

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
SE1_3	51	4	7	5.96	.720
SE2_3	51	4	7	5.94	.732
SE3_3	51	3	7	5.86	.960
SE4_3	51	2	7	5.84	.987
Valid N (listwise)	51				

Tables 22, 23, and 24 present information about past experiences, familiarity, and self-efficacy of using the recommendation system in the case of treatment 3: getting printer purchase advices from the content-based recommendation system.

Table 22. Past experiences for the treatment 4

Past experiences in the treatment 4

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never Use	9	17.6	17.6	17.6
	Rarely Use	16	31.4	31.4	49.0
	Sometimes Use	21	41.2	41.2	90.2
	Often Use	5	9.8	9.8	100.0
	Total	51	100.0	100.0	

Table 23. Familiarity for the treatment 4

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Familiarity1_4	51	1	7	4.78	1.736
Familiarity2_4	51	1	7	5.06	1.618
Valid N (listwise)	51				

Table 24. Self-efficacy for the treatment 4

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
SE1_4	51	3	7	5.80	.895
SE2_4	51	2	7	5.71	.965
SE3_4	51	3	7	5.84	.903
SE4_4	51	3	7	5.73	1.002
Valid N (listwise)	51				

4.2.2 Instrument Quality Analysis

4.2.2.1Descriptive Statistics

Tables 25, 26, 27, and 28 present the means and standard deviations of the dependent and independent variables for four treatments respectively.

Table 25. Descriptive statistics for the treatment 1, PLS output

Construct	Indicator	Mean	Stedv
PE	PE1_1	5.52	1.119
PE	PE2_1	5.54	1.237
PE	PE3_1	5.49	1.046
PE	PE4_1	5.27	1.167
EE	EE1_1	5.64	0.867
EE	EE2_1	5.88	0.886
EE	EE3_1	5.70	0.922
EE	EE4_1	5.86	0.872
SI	SI1_1	5.25	1.055
SI	SI2_1	5.29	1.10
SI	SI3_1	5.03	1.076
SI	SI4_1	5.03	1.319
TRUST	TRUST1_1	4.23	1.632
TRUST	TRUST2_1	4.88	1.125
TRUST	TRUST3_1	4.90	1.284
BI	BI1_1	5.09	1.187
BI	BI2_1	5.33	1.070
BI	BI3_1	4.98	1.157

Table 26. Descriptive statistics for the treatment 2, PLS output

Construct	Indicator	Mean	Stedv
PE	PE1_2	5.52	0.966
PE	PE2_2	5.64	0.996
PE	PE3_2	5.50	0.902
PE	PE4_2	5.31	1.122
EE	EE1_2	5.82	0.817
EE	EE2_2	5.98	0.860
EE	EE3_2	5.90	0.854
EE	EE4_2	6.05	0.925
SI	SI1_2	5.27	0.960
SI	SI2_2	5.33	1.194
SI	SI3_2	5.07	1.246
SI	SI4_2	5.27	1.372
TRUST	TRUST1_2	4.33	1.704
TRUST	TRUST2_2	5.00	1.131
TRUST	TRUST3_2	5.07	1.262
BI	BI1_2	5.11	1.336
BI	BI2_2	5.23	1.320

Table 26. (continued)

Construct	Indicator	Mean	Stedv
BI	BI3_2	5.01	1.334

Table 27. Descriptive statistics for the treatment 3, PLS output

Construct	Indicator	Mean	Stedv
PE	PE1_3	5.76	1.159
PE	PE2_3	5.70	1.204
PE	PE3_3	5.66	1.089
PE	PE4_3	5.68	1.140
EE	EE1_3	5.76	1.011
EE	EE2_3	5.86	0.916
EE	EE3_3	5.94	0.881
EE	EE4_3	6.03	0.870
SI	SI1_3	5.50	0.924
SI	SI2_3	5.52	1.137
SI	SI3_3	5.37	1.148
SI	SI4_3	5.43	1.284
TRUST	TRUST1_3	4.41	1.757
TRUST	TRUST2_3	4.90	1.389
TRUST	TRUST3_3	5.17	1.244
BI	BI1_3	4.90	1.284
BI	BI2_3	5.21	1.171
BI	BI3_3	4.72	1.327

Table 28. Descriptive statistics for the treatment 4, PLS output

Construct	Indicator	Mean	Stedv
PE	PE1_4	5.70	1.136
PE	PE2_4	5.50	1.461
PE	PE3_4	5.54	1.188
PE	PE4_4	5.37	1.413
EE	EE1_4	5.78	0.965
EE	EE2_4	5.98	0.836
EE	EE3_4	5.88	1.051
EE	EE4_4	6.09	1.005
SI	SI1_4	5.39	0.939
SI	SI2_4	5.52	1.046
SI	SI3_4	5.41	1.003
SI	SI4_4	5.41	1.098
TRUST	TRUST1_4	4.21	1.724
TRUST	TRUST2_4	4.92	1.309
TRUST	TRUST3_4	5.11	1.336
BI	BI1_4	4.74	1.572
BI	BI2_4	5.01	1.489
BI	BI3_4	4.62	1.413

4.2.2.2 Validity

Construct validity is normally evaluated with three forms of validity: content, convergent, and discriminant validity. Confirmatory Factor Analysis (CFA) method was used in this study to verify the uni-dimensionality, convergent validity, and discriminant validity of the scale.

Content validity assesses if the measurement represents all the dimensions of the construct. This study meets content validity by establishing the items through a careful assessment of available theories and previous empirical studies and discussing with academic professors who have expertise in the field of technology acceptance.

Convergent validity was tested using CFA with Visual PLS to verify uni-dimensionality. With the exception of SI3 (a business professor would recommend using this recommendation system) in the treatment 3 and 4 respectively, all other item loadings were found to be acceptable with loadings being .70 or higher in four treatments. Thus, SI3 was dropped from the treatment 3 and 4 due to the lower factor loading (<.70). Tables 29, 30, 31, and 32 present the results of item loading. Additionally, the AVE (Average Variance Extracted) of all dimensions should exceed .50 (Fornell &Larcker, 1981). The AVE of all dimensions was found to be acceptable. Tables 33, 34, 35, and 36 illustrate the results of the AVE. Besides, the square roots of the AVE from the constructs were higher than the correlation across constructs, supporting discriminant and convergent validity. Results of discriminant validity are shown in Tables 37, 38, 39, and 40.

Table 29. Item loading for the treatment 1, PLS output

Construct	Indicator	Loading
PE	PE1_1	0.94
PE	PE2_1	0.91
PE	PE3_1	0.90
PE	PE4_1	0.91
EE	EE1_1	0.85
EE	EE2_1	0.89
EE	EE3_1	0.92
EE	EE4_1	0.82
SI	SI1_1	0.82
SI	SI2_1	0.85
SI	SI3_1	0.77
SI	SI4_1	0.85
TRUST	TRUST1_1	0.86

Table 29. (continued)

TRUST	TRUST2_1	0.94
TRUST	TRUST3_1	0.94
BI	BI1_1	0.95
BI	BI2_1	0.92
BI	BI3_1	0.94

Table 30. Item loadings for the treatment 2, PLS output

Construct	Indicator	Loading
PE	PE1_2	0.86
PE	PE2_2	0.89
PE	PE3_2	0.87
PE	PE4_2	0.80
EE	EE1_2	0.92
EE	EE2_2	0.88
EE	EE3_2	0.89
EE	EE4_2	0.87
SI	SI1_2	0.73
SI	SI2_2	0.84
SI	SI3_2	0.85
SI	SI4_2	0.85
TRUST	TRUST1_2	0.75
TRUST	TRUST2_2	0.91
TRUST	TRUST3_2	0.92
BI	BI1_2	0.97
BI	BI2_2	0.96
BI	BI3_2	0.96

Table 31. Item loadings for the treatment 3, PLS output

Construct	Indicator	Loading
PE	PE1_3	0.90
PE	PE2_3	0.83
PE	PE3_3	0.90
PE	PE4_3	0.93
EE	EE1_3	0.91
EE	EE2_3	0.86
EE	EE3_3	0.90
EE	EE4_3	0.88
SI	SI1_3	0.79
SI	SI2_3	0.85
SI	**SI3_3**	**0.67 dropped**
SI	SI4_3	0.86
TRUST	TRUST1_3	0.73
TRUST	TRUST2_3	0.94
TRUST	TRUST3_3	0.92
BI	BI1_3	0.93
BI	BI2_3	0.88
BI	BI3_3	0.91

Table 32. Item loadings for the treatment 4, PLS output

Construct	Indicator	Loading
PE	PE1_4	0.90
PE	PE2_4	0.87
PE	PE3_4	0.91
PE	PE4_4	0.87
EE	EE1_4	0.84
EE	EE2_4	0.83
EE	EE3_4	0.94
EE	EE4_4	0.88
SI	SI1_4	0.75
SI	SI2_4	0.86
SI	**SI3_4**	**0.69 dropped**
SI	SI4_4	0.80
TRUST	TRUST1_4	0.79
TRUST	TRUST2_4	0.93
TRUST	TRUST3_4	0.91
BI	BI1_4	0.94
BI	BI2_4	0.94
BI	BI3_4	0.97

Table 33. AVE for the treatment 1, PLS output

Construct	AVE
PE	0.84
EE	0.76
SI	0.68
TRUST	0.84
BI	0.89

Table 34. AVE for the treatment 2, PLS output

Construct	AVE
PE	0.74
EE	0.80
SI	0.67
TRUST	0.75
BI	0.93

Table 35. AVE for the treatment 3, PLS output

Construct	AVE
PE	0.80
EE	0.79
SI	0.74
TRUST	0.76
BI	0.83

Table 36. AVE for the treatment 4, PLS output

Construct	AVE
PE	0.79
EE	0.76
SI	0.69
TRUST	0.78
BI	0.91

Table 37. Correlation of constructs for the treatment 1, PLS output

Construct	PE	EE	SI	TRUST	BI
PE	0.92				
EE	0.41	0.87			
SI	0.72	0.52	0.82		
TRUST	0.62	0.28	0.60	0.91	
BI	0.65	0.32	0.50	0.61	0.94

Note: Diagonal elements are the square root of the shared variance between the constructs and their measures; off-diagonal elements are correlations between constructs.

Table 38. Correlation of constructs for the treatment 2, PLS output

Construct	PE	EE	SI	TRUST	BI
PE	0.86				
EE	0.56	0.89			
SI	0.61	0.52	0.82		
TRUST	0.66	0.32	0.58	0.89	
BI	0.51	0.40	0.46	0.32	0.96

Note: Diagonal elements are the square root of the shared variance between the constructs and their measures; off-diagonal elements are correlations between constructs.

Table 39. Correlation of constructs for the treatment 3, PLS output

Construct	PE	EE	SI	TRUST	BI
PE	0.89				
EE	0.52	0.89			
SI	0.68	0.53	0.86		
TRUST	0.58	0.44	0.61	0.87	
BI	0.53	0.49	0.65	0.60	0.91

Note: Diagonal elements are the square root of the shared variance between the constructs and their measures; off-diagonal elements are correlations between constructs.

Table 40. Correlation of constructs for the treatment 4, PLS output

Construct	PE	EE	SI	TRUST	BI
PE	0.91				
EE	0.69	0.87			
SI	0.77	0.56	0.83		
TRUST	0.74	0.53	0.64	0.88	
BI	0.70	0.59	0.69	0.68	0.95

Note: Diagonal elements are the square root of the shared variance between the constructs and their measures; off-diagonal elements are correlations between constructs.

4.2.2.3 Reliability

Cronbach's alphas and the value of composite reliability were used to measure the internal consistency of scale items. All internal consistency reliabilities and Cronbach's α for four treatments were found to be acceptable. The results are found in Tables 41, 42, 43, and 44.

Table 41. Reliability results for the treatment 1, PLS output

Construct	Composite Reliability	Cronbach's α
PE	0.95	0.93
EE	0.92	0.89
SI	0.89	0.84
TRUST	0.94	0.88
BI	0.96	0.93

Table 42. Reliability results for the treatment 2, PLS output

Construct	Composite Reliability	Cronbach's α
PE	0.92	0.87
EE	0.94	0.91
SI	0.89	0.83
TRUST	0.90	0.80
BI	0.97	0.96

Table 43. Reliability results for the treatment 3, PLS output

Construct	Composite Reliability	Cronbach's α
PE	0.94	0.91
EE	0.93	0.91
SI	0.89	0.81
TRUST	0.90	0.81
BI	0.93	0.89

Table 44. Reliability results for the treatment 4, PLS output

Construct	Composite Reliability	Cronbach's α
PE	0.93	0.90
EE	0.93	0.89
SI	0.87	0.77
TRUST	0.91	0.84
BI	0.97	0.95

4.2.3 Hypothesis Testing

The hypothesis testing was divided into three stages. The first stage only examined the original model without considering any moderating influences to test hypotheses from 1 to 4. The moderating influences were added in the second stage to examine hypotheses from 5 to 13. R^2 value was calculated to evaluate the predictive power of the structural model and this value also indicates the amount of variance explained by the exogenous variables. PLS (Visual PLS, Version 1.04) was used to examine the research model. A bootstrapping method was performed to evaluate hypothesized relationships. The testing of stage one and two was performed for four treatments separately. The third stage examined the pooled data of four treatments.

4.2.3.1 Model Testing Without Moderators

For collaborative filtering recommendation system with the MP3 player, PE and TRUST both impacted behavioral intention to use the recommendation system, supporting H1 and H4. On the other hand, BI was not influenced by EE and SI, thereby providing no support for H2 and H3. The summary of model testing for the treatment 1 is shown in Table 45.

Table 45. Model testing without moderators for the treatment 1

	Behavioral Intention	
	R^2 value=0.499	
(N=51)	ß	t-value
PE	0.462	**2.687****
EE	0065	0.749
SI	-0.067	-0.637
TRUST	0.344	**2.313***

Notes: 1. *p <.05; **p<.01; ***p<.001.
2. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; TRUST: Trust

For collaborative filtering recommendation system with the printer, PE, EE, SI, and TRUST didn't affect behavioral intention to use the recommendation system, not supporting H1, H2, H3, and H4. The summary of model testing for the treatment 2 is listed in Table 46.

Table 46. Model testing without moderators for the treatment 2

	Behavioral Intention	
	R^2 value=0.312	
(N=51)	ß	t-value
PE	0.371	1.859
EE	0.105	0.950
SI	0.240	1.460
TRUST	-0.100	-0.857

Notes: 1. *p <.05; **p<.01; ***p<.001.
2. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; TRUST: Trust

For content-based recommendation with the MP3 player, all hypotheses were not confirmed, except for the proposed effect of SI on BI (H3). The summary of model testing for the treatment 3 is presented in Table 47.

Table 47. Model testing without moderators for the treatment 3

	Behavioral Intention	
	R^2 value=0.514	
(N=51)	ß	t-value
PE	0.059	0.641
EE	0137	1.341
SI	0.388	**2.755****
TRUST	0.259	1.736

Notes: 1. *p <.05; **p<.01; ***p<.001.
2. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; TRUST: Trust

For content-based recommendation with the printer, SI and TRUST had the significant direct effect on BI respectively, supporting H3 and H4. However, PE and EE did not affect BI, providing no support on H1 and H2. Table 48 provides the summary of model testing for the treatment 4.

Table 48. Model testing without moderators for the treatment 4

	Behavioral Intention	
	R^2 value=0.615	
(N=51)	ß	t-value
PE	0.140	1.009
EE	0.164	1.372
SI	0.313	**2.289***
TRUST	0.289	**2.115***

Notes: 1. *p <.05; **p<.01; ***p<.001.
2. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; TRUST: Trust

4.2.3.2 Model Testing With Moderators

In the second stage, moderators (gender and experience) were added in to examine their potential effects for the research model. Gender was coded as a 0/1 (0 is male and 1 is female) dummy variable. Experience was also operationalized via a dummy variable that took ordinal values of 0, 1, or 2 to represent different levels of experience in using recommendation systems (0 is low level, 1 is medium level, and 2 is high level). The k-means clustering was performed to categorize the moderator of experience. For the treatment 1, no hypotheses were confirmed on proposed effect of moderators. Table 49 presents the summary of model testing with moderators for the treatment1.

Table 49. Model testing with moderators for the treatment 1

	Behavioral Intention	
	R^2 value=0.618	
(N=51)	ß	t-value
PE	0.404	1.4925
EE	0.165	1.145
SI	-0.006	-0.0495
TRUST	0.185	1.03
PExGEN	-0.126	-0.7662
EExGEN	0.155	1.0667
SIxGEN	0.261	1.5535
TRUSTxGEN	-0.154	-1.095
EExEXP	0.008	0.0649
SIxEXP	-0.099	-0.8966
TRUSTxEXP	0.098	0.5291

Notes: 1. *p <.05; **p<.01; ***p<.001.
2. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; TRUST: Trust; GEN: Gen; EXP: Experience

For all proposed effect of moderators, only H8 was confirmed. The summary of model testing with moderators for the treatment2 is listed in Table 50.

Table 50. Model testing with moderators for the treatment 2

	Behavioral Intention	
	R^2 value=0.444	
(N=51)	ß	t-value
PE	0.116	0.547
EE	0.126	0.736
SI	0.381	1.79
TRUST	-0.175	-0.832
PExGEN	-0.197	-0.853
EExGEN	0.209	1.186
SIxGEN	0.315	1.625
TRUSTxGEN	-0.368	**-2.173***
EExEXP	0.068	0.307
SIxEXP	-0.054	-0.312
TRUSTxEXP	0.087	0.423

Notes: 1. *p <.05; **p<.01; ***p<.001.
2. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; TRUST: Trust; GEN: Gender; EXP: Experience

The results did not support any proposed path of moderators in treatment 3. Table 51 presents the summary of model testing with moderators for the treatment3.

Table 51. Model testing with moderators for the treatment 3

	Behavioral Intention	
	R^2 value=0.576	
(N=51)	ß	t-value
PE	0.107	0.5374
EE	0.060	0.4602
SI	0.377	**2.125***
TRUST	0.26	1.5619
PExGEN	-0.264	-1.1847
EExGEN	0.245	1.2981
SIxGEN	0.03	0.227
TRUSTxGEN	0.056	0.4423
EExEXP	0.221	1.2849
SIxEXP	-0.08	-0.5311
TRUSTxEXP	0.083	0.497

Notes: 1. *p <.05; **p<.01; ***p<.001.
2. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; TRUST: Trust; GEN: Gender; EXP: Experience

The hypotheses from H5 to H13 were not confirmed in treatment 4. Table 52 presents the summary of model testing with moderators for the treatment4.

Table 52. Model testing with moderators for the treatment 4

	Behavioral Intention	
	R^2 value=0.657	
(N=51)	ß	t-value
PE	0.148	0.856
EE	0.147	0.862
SI	0.307	1.705
TRUST	0.245	1.361
PExGEN	0.119	0.665
EExGEN	0.176	0.978
SIxGEN	-0.228	-1.503
TRUSTxGEN	-0.033	-0.258
EExEXP	0.080	0.370
SIxEXP	0.130	0.837
TRUSTxEXP	-0.132	-0.722

Notes: 1. *p <.05; **p<.01; ***p<.001.
2. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; TRUST: Trust; GEN: Gender; EXP: Experience

4.2.3.3 Pooled Case without Moderators

The Chow's test was conducted first to examine if the pooled data can be used to examine the combined model. Table 53 presents results of the Chow's test. Treatment*PE, Treatment*EE, Treatment*SI, and Treatment*Trust are results of the Chow's test. All results are nonsignificant, meaning that the pooled data can be used to examine the combined model.

Table 53. Chow's test for the pooled data

Tests of Between-Subjects Effects

Dependent Variable: BI

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	145.478[a]	16	9.092	10.315	.000
Intercept	.654	1	.654	.742	.390
PE	9.536	1	9.536	10.819	.001
EE	3.385	1	3.385	3.841	.052
SI	4.248	1	4.248	4.820	.029
Trust	7.282	1	7.282	8.261	.005
Treatment * PE	2.376	3	.792	.899	.443
Treatment * EE	.860	3	.287	.325	.807
Treatment * SI	2.781	3	.927	1.052	.371
Treatment * Trust	2.991	3	.997	1.131	.338
Error	162.188	184	.881		
Total	5329.333	201			
Corrected Total	307.666	200			

a. R Squared = .473 (Adjusted R Squared = .427)

With the results of the Chow's test, the pooled data from four treatments (simple size of 204) is used to examine relationships across various dimensions. All hypotheses were confirmed except for the proposed effect of EE on BI (H2). The summary of model testing for the pooled case is presented in Table 54.

Table 54. Model testing without moderators for the pooled case

	Behavioral Intention	
	R^2 value=0.425	
(N=204)	ß	t-value
PE	0.266	**2.723****
EE	0.129	1.988
SI	0.157	**2.229***
TRUST	0.223	**2.930****

Notes: 1. *p <.05; **p<.01; ***p<.001.
2. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; TRUST: Trust

4.2.3.4 Pooled Case with Moderators

In additional to moderators of sex and experience, type of product was also added in the pooled case. Type of product was coded as a 0/1 (0 is utilitarian product and 1 is hedonic one) dummy variable. For all proposed effect of moderators, only H8 was confirmed. Table 55 presents the summary of pooled case with moderators.

Table 55. Model testing with moderators for the pooled case

	Behavioral Intention	
	R^2 value=0.489	
(N=204)	ß	t-value
PE	0.233	**2.3602***
EE	0.117	1.7054
SI	0.209	**2.4314***
TRUST	0.183	**2.357***
PExGEN	-0.143	-1.7157
EExGEN	-0.086	-1.3535
SIxGEN	-0.076	-0.954
TRUSTxGEN	0.147	**2.1394***
EExEXP	0.05	1.0268
SIxEXP	-0.048	-0.6956
TRUSTxEXP	0.07	1.1578
PExPRO	0.109	1.3132
TRUSTxPRO	-0.047	-0.7124

Notes: 1. *p <.05; **p<.01; ***p<.001.
2. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; TRUST: Trust; GEN: Gender; EXP: Experience; PRO: Product

4.2.4 Hypothesis Results Summary

The results of the hypothesis testing for four treatments and the pooled case can be found in Tables 56-60.

Table 56. Hypothesis testing results for the treatment 1

HYPOTHESIS	RESULT	HYPOTHESIS	RESULT
H1. Performance expectancy will have a positive effect on intention to use the recommendation system.	S	H8. The effect of trust on intention to use the recommendation system will be moderated by the sex of the user.	NS
H2. Effort expectancy of the recommendation system will have a positive effect on intention to use the recommendation system.	NS	H9. The effect of effort expectancy on intention to use the recommendation system will be moderated by experience.	NS
H3. Social influence will have a positive effect on intention to use the recommendation system.	NS	H10. The effect of social influence on intention to use the recommendation system will be moderated by experience.	NS
H4. Trust in the recommendation system will have a positive effect on intention to use the recommendation system.	S	H11. The effect of trust on intention to use the recommendation system will be moderated by experience.	NS
H5. The effect of performance expectancy on intention to use the recommendation system will be moderated by the sex of the user.	NS	H12. The effect of performance on intention to use the recommendation system will be moderated by product types.	NS

Table 56. (continued)

H6. The effect of effort expectancy on intention to use the recommendation system will be moderated by the sex of the user	NS	H13. The effect of trust on intention to use the recommendation system will be moderated by product types.	NS
H7. The effect of social influence on intention to use the recommendation system will be moderated by the sex of the user.	NS		

Table 57. Hypothesis testing results for the treatment 2

HYPOTHESIS	RESULT	HYPOTHESIS	RESULT
H1. Performance expectancy will have a positive effect on intention to use the recommendation system.	NS	H8. The effect of trust on intention to use the recommendation system will be moderated by the sex of the user.	S
H2. Effort expectancy of the recommendation system will have a positive effect on intention to use the recommendation system.	NS	H9. The effect of effort expectancy on intention to use the recommendation system will be moderated by experience.	NS
H3. Social influence will have a positive effect on intention to use the recommendation system.	NS	H10. The effect of social influence on intention to use the recommendation system will be moderated by experience.	NS
H4. Trust in the recommendation system will have a positive effect on intention to use the recommendation system.	NS	H11. The effect of trust on intention to use the recommendation system will be moderated by experience.	NS
H5. The effect of performance expectancy on intention to use the recommendation system will be moderated by the sex of the user.	NS	H12. The effect of performance on intention to use the recommendation system will be moderated by product types.	NS
H6. The effect of effort expectancy on intention to use the recommendation system will be moderated by the sex of the user.	NS	H13. The effect of trust on intention to use the recommendation system will be moderated by product types.	NS
H7. The effect of social influence on intention to use the recommendation system will be moderated by the sex of the user.	NS		

Table 58. Hypothesis testing results for the treatment 3

HYPOTHESIS	RESULT	HYPOTHESIS	RESULT
H1. Performance expectancy will have a positive effect on intention to use the recommendation system.	NS	H8. The effect of trust on intention to use the recommendation system will be moderated by the sex of the user.	NS
H2. Effort expectancy of the recommendation system will have a positive effect on intention to use the recommendation system.	NS	H9. The effect of effort expectancy on intention to use the recommendation system will be moderated by experience.	NS
H3. Social influence will have a positive effect on intention to use the recommendation system.	S	H10. The effect of social influence on intention to use the recommendation system will be moderated by experience.	NS
H4. Trust in the recommendation system will have a positive effect on intention to use the recommendation system.	NS	H11. The effect of trust on intention to use the recommendation system will be moderated by experience.	NS
H5. The effect of performance expectancy on intention to use the recommendation system will be moderated by the sex of the user.	NS	H12. The effect of performance on intention to use the recommendation system will be moderated by product types.	NS
H6. The effect of effort expectancy on intention to use the recommendation system will be moderated by the sex of the user.	NS	H13. The effect of trust on intention to use the recommendation system will be moderated by product types.	NS
H7. The effect of social influence on intention to use the recommendation system will be moderated by the sex of the user.	NS		

Table 59. Hypothesis Testing Results for the treatment 4

HYPOTHESIS	RESULT	HYPOTHESIS	RESULT
H1. Performance expectancy will have a positive effect on intention to use the recommendation system.	NS	H8. The effect of trust on intention to use the recommendation system will be moderated by the sex of the user.	NS
H2. Effort expectancy of the recommendation system will have a positive effect on intention to use the recommendation system.	NS	H9. The effect of effort expectancy on intention to use the recommendation system will be moderated by experience.	NS
H3. Social influence will have a positive effect on intention to use the recommendation system.	S	H10. The effect of social influence on intention to use the recommendation system will be moderated by experience.	NS
H4. Trust in the recommendation system will have a positive effect on intention to use the recommendation system.	S	H11. The effect of trust on intention to use the recommendation system will be moderated by experience.	NS

Table 59. (continued)

H5. The effect of performance expectancy on intention to use the recommendation system will be moderated by the sex of the user.	NS	H12. The effect of performance on intention to use the recommendation system will be moderated by product types.	NS
H6. The effect of effort expectancy on intention to use the recommendation system will be moderated by the sex of the user.	NS	H13. The effect of trust on intention to use the recommendation system will be moderated by product types.	NS
H7. The effect of social influence on intention to use the recommendation system will be moderated by the sex of the user.	NS		

Table 60. Hypothesis testing results for the pooled case

HYPOTHESIS	RESULT	HYPOTHESIS	RESULT
H1. Performance expectancy will have a positive effect on intention to use the recommendation system.	S	H8. The effect of trust on intention to use the recommendation system will be moderated by the sex of the user.	S
H2. Effort expectancy of the recommendation system will have a positive effect on intention to use the recommendation system.	NS	H9. The effect of effort expectancy on intention to use the recommendation system will be moderated by experience.	NS
H3. Social influence will have a positive effect on intention to use the recommendation system.	S	H10. The effect of social influence on intention to use the recommendation system will be moderated by experience.	NS
H4. Trust in the recommendation system will have a positive effect on intention to use the recommendation system.	S	H11. The effect of trust on intention to use the recommendation system will be moderated by experience.	NS
H5. The effect of performance expectancy on intention to use the recommendation system will be moderated by the sex of the user.	S	H12. The effect of performance on intention to use the recommendation system will be moderated by product types.	NS
H6. The effect of effort expectancy on intention to use the recommendation system will be moderated by the sex of the user.	NS	H13. The effect of trust on intention to use the recommendation system will be moderated by product types.	NS
H7. The effect of social influence on intention to use the recommendation system will be moderated by the sex of the user.	NS		

CHAPTER 5. DISCUSSION AND CONCLUSIONS

5.1 Overview

The objective of the study was to present and validate a modified UTAUT model to examine its relevance and the important role of trust on behavioral intention to use recommendation systems in the context of e-commerce. Concerning different effects of hedonic and utilitarian product, this study also took into account of hedonic and utilitarian characteristics to determine their effects on customer use of recommendation systems. Based on two types of products (hedonic and utilitarian) and two types of recommendation systems (collaborative filtering and content-based), this study presented a 2 (recommendation systems) x 2 (products) treatments. These four treatments, along with the pooled case of these four treatments (simple size of 204), were investigated using a modified UTAUT model. With empirical analysis, we may reasonably conclude that different types of recommendation systems and products did have different effects on customer intention to use recommendation systems.

Specifically, our findings are not in contradiction with those of technology acceptance related studies discussed above. Like the original UTAUT model, the study showed statistical significance on the proposed effect of PE on BI in the treatment 1 (collaborative filtering with the MP3 player) and the pooled case. A general interpretation for there being no statistical significance of PE on BI in the rest of treatments may lie in fundamental differences of two types of recommendation systems and products.

For the proposed effect of EE on BI part, there was the lack of statistical significance for the effect of EE on BI in any treatment, including the pooled one. One reason to account for this may lie in the fact that most of participants showed a medium or high degree of experience of using recommendation systems in any treatment. The effect of effort expectancy is significant during the first time period of accepting the technology; however, it becomes nonsignificant over period of extended and sustained usage (Davis et al., 1989; Thompson et al., 1991; 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 suggest that SI do matter in the case of content-based recommendation system and the pooled case. Therefore, it is apparent that a potential user of the content-based recommendation 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 these who use the collaborative filtering recommendation system.

Trust is emerging as an important aspect of technology acceptance as an interesting number of technologies engage in privacy issues over the web. However, trust has not been examined very much in the widely used models explaining technology acceptance like the UTAUT. Data from the study lead us to believe that providers of online recommendation systems should notice the importance of trust. Trust appeared to play an important role in both types of recommendation systems. Thus, this result implies that a customer's intention to use recommendation systems depends not only on the operational characteristics of the recommendation system, its PE or EE, but also, and possibly to a greater degree, on customer trust in the provider of the recommendation system. Providers of these systems need to take into account their recommendation systems planning efforts.

5.2 Implications

From a theoretical perspective, this study contributes to the field's understanding of the various factors influencing people's intentions to use recommendation systems as they face the issue of information overload in the context of e-commerce by using a modified UTAUT model. The results of this study prove the relevance of UTAUT in accepting online recommendation systems.

This study also suggests a new perspective for the UTAUT model in general. In this line of research, researchers focus more on expected outcome of operational characteristics, such as performance expectancy or effort expectancy. The concept of trust did not show up in this line of research. Due to highly competitive environment, more and more providers of innovative technology try to provide the most customized services to maintain competitive advantage in online environments. However, because of high uncertainty for providers of technologies, users may not intend to use these technologies until they trust these providers of technologies. With this in mind, the concept of trust should be taken into consideration with the original UTAUT model. By integrating the concept of trust with the original UTAUT model successfully, this study represents a step forward in the overall model development.

From a practitioner point of view, this study has important practical implications for designers of effective online recommendation systems. The findings of this study indicate that participants had different perception for two types of recommendation systems. PE and Trust are two major concerns for those who use the collaborative filtering system. On the other hand, SI and Trust are another two major concerns for those who use the content-based recommendation system. Thus, managers should realize fundamental differences of two types of recommendation systems and make appropriate strategies when they try to invest on building an effective recommendation system. Additionally, although effort expectancy (EE) was lack of statistic significance in any treatment, 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 without so many experiences in using recommendation systems. Managers or designers should treat this part of result circumspectly. The ultimate goal of recommendation systems is to help customers find the most appropriate products and then bring more profits to providers of recommendation systems. Trust appears to an important role for both types of recommendation systems. Thus, designers must design a recommendation system where customers believe that the provider of this system will not take advantage of their weakness.

5.3 Limitations and Future Research

Even though this research has the undeniable merit of offering valuable insights into the process of recommendation systems acceptance, it has some limitations. First, this study only recruited 51 subjects to do the final study. While results presented desirable findings, more subjects, if possible, should be recruited to be more representative.

Second, 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.

Third, since the study analyzed recommendation systems from two well-known websites, it is unclear whether the results can be generalized to less-known websites. A replication of the study needs to take into consideration this issue.

This study only investigated people's intention to use recommendation 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 should also consider and analyze less-known websites to achieve the goal of generalizability.

APPENDIX A. PRODUCT MANIPULATION PILOT STUDY

1. Hedonic = fun, enjoyable, for pleasure
   Utilitarian = work related, get a job done, accomplishes a task or useful goal
   Please rate these items based on whether you consider each to be closer to being utilitarian or hedonic.

	Hedonic						Utilitarian
Cell Phone	1	2	3	4	5	6	7
Laptop	1	2	3	4	5	6	7
Digital Camera	1	2	3	4	5	6	7
Desktop	1	2	3	4	5	6	7
MP3 player	1	2	3	4	5	6	7
TV	1	2	3	4	5	6	7
Camcorder	1	2	3	4	5	6	7
Printer	1	2	3	4	5	6	7
GPS	1	2	3	4	5	6	7

2. Please rate these items based on whether you consider each to be closer to being exciting or dull.

	Exciting						Dull
Cell Phone	1	2	3	4	5	6	7
Laptop	1	2	3	4	5	6	7
Digital Camera	1	2	3	4	5	6	7
Desktop	1	2	3	4	5	6	7
MP3 player	1	2	3	4	5	6	7
TV	1	2	3	4	5	6	7
Camcorder	1	2	3	4	5	6	7
Printer	1	2	3	4	5	6	7
GPS	1	2	3	4	5	6	7

3. Please rate these items based on whether you consider each to be closer to being pleasant or unpleasant.

	Pleasant						Unpleasant
Cell Phone	1	2	3	4	5	6	7
Laptop	1	2	3	4	5	6	7
Digital Camera	1	2	3	4	5	6	7
Desktop	1	2	3	4	5	6	7
MP3 player	1	2	3	4	5	6	7
TV	1	2	3	4	5	6	7
Camcorder	1	2	3	4	5	6	7
Printer	1	2	3	4	5	6	7
GPS	1	2	3	4	5	6	7

4. Please rate these items based on whether you consider each to be closer to being interesting or boring.

	Interesting						Boring
Cell Phone	1	2	3	4	5	6	7
Laptop	1	2	3	4	5	6	7
Digital Camera	1	2	3	4	5	6	7
Desktop	1	2	3	4	5	6	7
MP3 player	1	2	3	4	5	6	7
TV	1	2	3	4	5	6	7
Camcorder	1	2	3	4	5	6	7
Printer	1	2	3	4	5	6	7
GPS	1	2	3	4	5	6	7

APPENDIX B. STUDY QUESTIONS

Pre-Survey

(administered before any of the four treatments)

Personal Information

1. Gender:
   - Male
   - Female
2. Age
   - Under 19 years
   - 20~25 years
   - 26~30 years
   - 31~35 years
   - 35~40 years
   - Over 40 years
3. Are you a US Citizen?
   - Yes
   - No
4. What is your ethnicity?
   - Hispanic or Latino
   - American Indian/Alaskan Native
   - Asian
   - Black or African American
   - Native Hawaiian or Other Pacific Islander
   - White
   - Other
5. Please answer the following questions based on your feelings about your current skills/assessments of utilizing online recommendation systems

	Strongly Disagree						Strongly Agree
I believe I have the ability to use recommendation systems to obtain a useful product recommendation.	1	2	3	4	5	6	7
I believe I have the ability to use recommendation systems to obtain a useful product recommendation.	1	2	3	4	5	6	7
I believe I have the ability to identify my personal product preferences in online recommendation systems to get an appropriate recommendation.	1	2	3	4	5	6	7
I believe I have the ability to evaluate and use the results of recommendation systems to make good product choices.	1	2	3	4	5	6	7

6. Please answer the following questions based on your experiences

	Strongly Disagree						Strongly Agree
I have previous experience purchasing printers online.	1	2	3	4	5	6	7
I have previous experience purchasing MP3 player online.	1	2	3	4	5	6	7

7. Please answer the following questions based on your intent

	Strongly Disagree						Strongly Agree
I plan to buy a printer online in the future.	1	2	3	4	5	6	7
I plan to buy a MP3 player online in the future.	1	2	3	4	5	6	7

8. If you have any experiences purchasing printers online, please list any brand of printer you bought before ____
9. If you do not have any experiences purchasing printers online, please list any brand of printer you may like or buy in the future___________________________________
10. If you have any experiences purchasing MP3 player online, please list any brand of MP3 player you bought before____
11. If you do not have any experiences purchasing MP3 player online, please list any brand of MP3 player you may like or buy in the future______________________________

Post-Treatment Surveys

(Each treatment was displayed to the user in random order with the same set of questions after each. For brevity, we show the first treatment followed by the questions and then show just the introduction for the other three treatments as the same set of questions was asked after each.)

Treatment 1:

Please experience Shopping.com first before doing the following survey. In this experiment, your main job is to pretend to buy a "MP3 Player" (under "Electronics" along the top). You can select any MP3 player to review based on your current preferences. After selecting a MP3 player you are interested in and going to its individual product page, you are allowed to review any information to help you make purchasing decisions on this page. The last step of the reviewing process is to select a MP3 player you are interested in from "People Who Shopped For This Also Shopped For..." area lying in the middle of every individual product page. You can select any MP3 player you are interested in from "People Who Shopped For This Also Shopped For..." area multiple times until you find the most appropriate MP3 player. The recommended result will be very similar as the following picture.

Once you have found the appropriate MP3 player, please move to the following questions.

Note that if you cannot find "People Who Shopped For This Also Shopped For..." area lying in the middle of any of your individual product page, please go back to the first page to reselect any camera you are interested in and reenter its product page. For most of MP3 player, the system will provide this recommendation function. However, for very few MP3 player, especially for those that are not highly purchased, the system will "not" provide this function because no related information about these MP3 player is available.

Please answer the following questions based on your feelings/attitudes about your previous experiences and frequencies of utilizing this type of online recommendation system (prior to performing the above task)

1. How often do you use this type of online recommendation system or similar system?

- Never Use
- Seldom Use
- Sometimes Use
- Often Use

2.

	Strongly Disagree						Strongly Agree
I am familiar with this type of online recommendation system or similar system.	1	2	3	4	5	6	7

3.

	Strongly Disagree						Strongly Agree
I am familiar with searching the recommendations in this type of online recommendation system or similar system.	1	2	3	4	5	6	7

4. Please answer the following questions based on your feelings about your current skills/assessments of utilizing online recommendation systems

	Strongly Disagree						Strongly Agree
I believe I have the ability to use recommendation systems to obtain a useful product recommendation.	1	2	3	4	5	6	7
I believe I have the ability to use recommendation systems to obtain a useful product recommendation.	1	2	3	4	5	6	7
I believe I have the ability to identify my personal product preferences in online recommendation systems to get an appropriate recommendation.	1	2	3	4	5	6	7
I believe I have the ability to evaluate and use the results of recommendation systems to make good product choices.	1	2	3	4	5	6	7

5. Please answer the following questions based on your feelings/attitudes about using this type of system to receive purchasing recommendations

	Strongly Disagree						Strongly Agree
I would find the recommendation system useful in searching and finding items.	1	2	3	4	5	6	7
Using the recommendation system enables me to search and find items more quickly.	1	2	3	4	5	6	7
Using the recommendation system increases my productivity in searching and finding items.	1	2	3	4	5	6	7
If I use the recommendation system, I will increase my chances of getting better purchasing advice.	1	2	3	4	5	6	7

6. Please answer the following questions based on your feelings/attitudes about using this type of system to receive purchasing recommendations

	Strongly Disagree						Strongly Agree
My interaction with the recommendation system is clear and understandable.	1	2	3	4	5	6	7
It would be easy for me to become skillful at using the recommendation system.	1	2	3	4	5	6	7
I would find the recommendation system easy to use.	1	2	3	4	5	6	7
Learning to operate the recommendation system is easy for me.	1	2	3	4	5	6	7

7. Please answer the following questions based on your feelings/attitudes about using this type of system to receive purchasing recommendations

	Strongly Disagree						Strongly Agree
Friends of mine would also find this system attractive.	1	2	3	4	5	6	7
People whose opinion I value would be in favor of using this system.	1	2	3	4	5	6	7
A business professor would recommend using this recommendation system.	1	2	3	4	5	6	7
I believe that expert computer users would recommend this system.	1	2	3	4	5	6	7

8. Please answer the following questions based on your feelings/attitudes about using this type of system to receive purchasing recommendations

	Strongly Disagree						Strongly Agree
I intend to use this type of recommendation system in the next 6 months.	1	2	3	4	5	6	7
I predict I will use this type of recommendation system in the next 6 months.	1	2	3	4	5	6	7
I plan to use this type of recommendation system in the next 6 months.	1	2	3	4	5	6	7

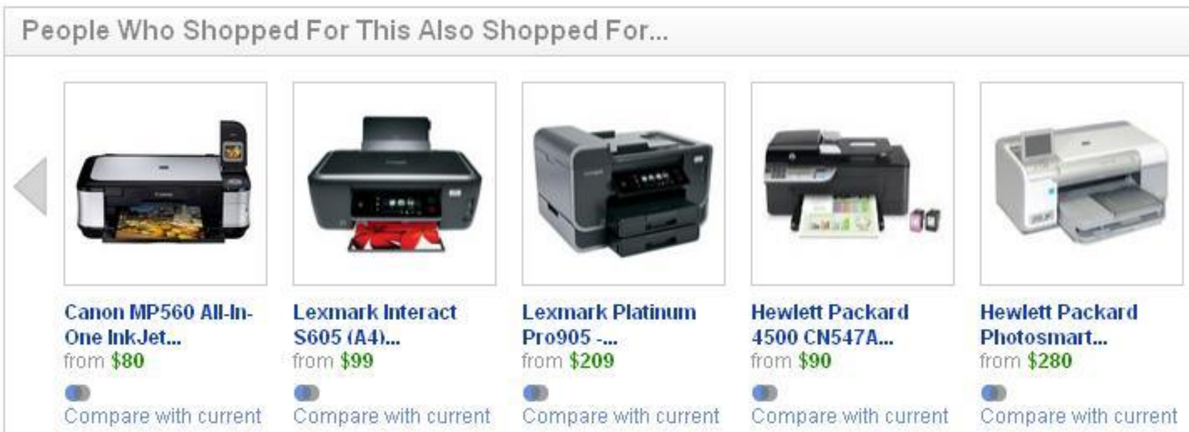
9. Please answer the following questions based on your feelings/attitudes about using this type of system to receive purchasing recommendations

	Strongly Disagree						Strongly Agree
Even if the system were not monitored, I would trust the recommendation system to recommend appropriate items.	1	2	3	4	5	6	7

I trust the recommendation system.	1	2	3	4	5	6	7
I trust that the system makes reliable recommendations.	1	2	3	4	5	6	7

Treatment 2:

Please experience Shopping.com first before doing the following survey. In this experiment, your main job is to pretend to buy a "Printer" (under "Computers" along the top). You can select any printer to review based on your current preferences. After selecting a printer you are interested in and going to its individual product page, you are allowed to review any information to help you make purchasing decisions on this page. The last step of the reviewing process is to select any printer you are interested in from "People Who Shopped For This Also Shopped For..." area lying in the middle of every individual product page. You can select any printer you are interested in from "People Who Shopped For This Also Shopped For..." area multiple times until you find the most appropriate printer.
The recommended result will be very similar as the following picture.

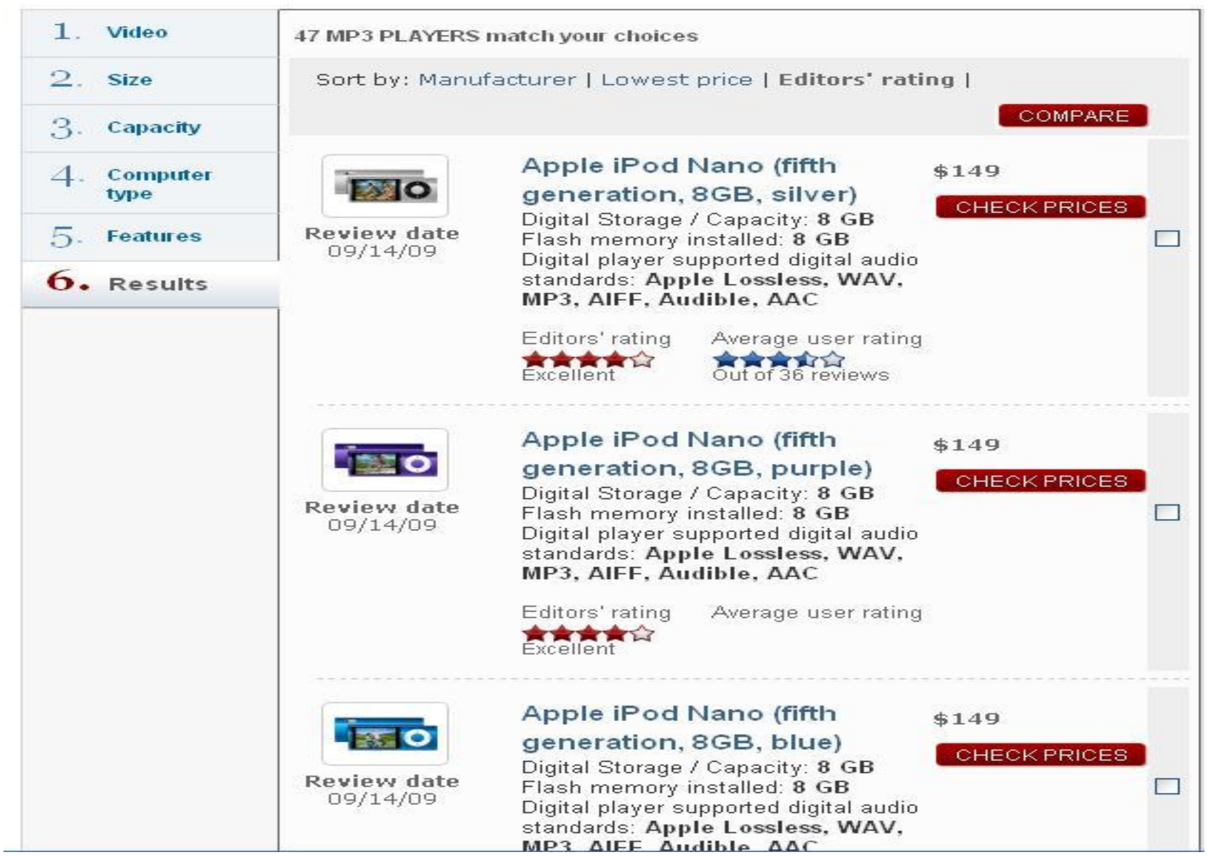


Once you have found the appropriate printer, please move to the following questions.

Note that if you cannot find "People Who Shopped For This Also Shopped For..." area lying in the middle of any of your individual product page, please go back to the first page to reselect any printer you are interested in and reenter its product page. For most of printers, the system will provide this recommendation function. However, for very few printers, especially for those that are not highly purchased, the system will "not" provide this function because no related information about these printers is available.
Please answer the following questions based on your feelings/attitudes about your previous experiences and frequencies of utilizing this type of online recommendation system (prior to performing the above task)

Treatment 3:
Please experience [CNET Reviews] first before doing the following survey. In this experiment, your main job is to evaluate if "MP3 player product finder" function helps you find the most appropriate MP3 player. You need to select "MP3 player" category (under "All Categories" along the top). Once you've entered "MP3 player" category, you need to select the "MP3 player product finder" function under "MP3 PLAYER BUYING ADVICE" area lying in the middle of the page to express your personal preference. While searching for a MP3 player, you are allowed to express or refine your personal preferences to get the most personalized product recommendations as the researcher did in the demo section. You are also allowed to review any recommended MP3 player showing in the "Results" section.

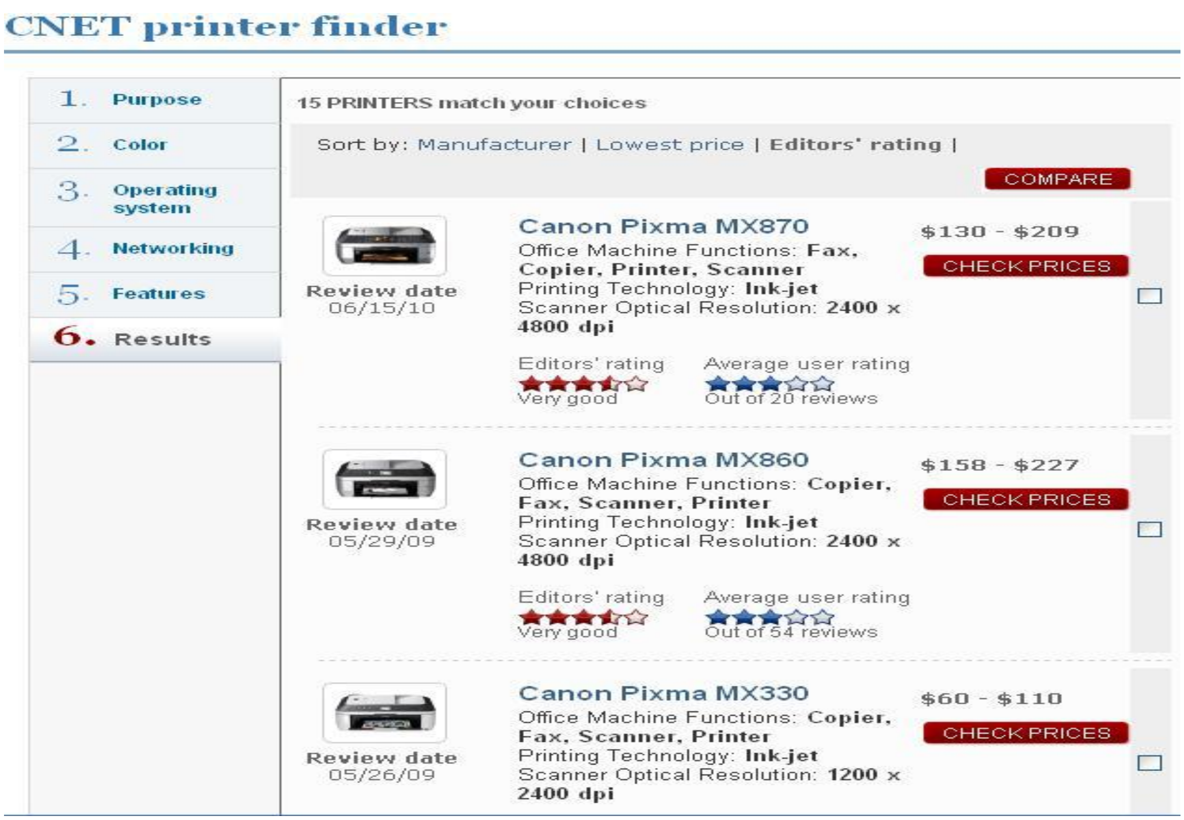
The recommended result will be very similar as the following picture.



Please answer the following questions based on your feelings/attitudes about your previous experiences and frequencies of utilizing this type of online recommendation system (prior to performing the above task)

Treatment 4:
Please experience CNET Reviews first before doing the following survey. In this experiment, your main job is to evaluate if "Printer finder" function helps you find the most appropriate printer. You need to select the "Printers" category (under "All Categories" along the top) to launch the whole process. Once you've entered "Printer" category, you need to use "Printer finder" function under "PRINTER BUYING ADVICE" area lying in the middle of page to express your personal preference. While searching for a printer, you are allowed to express or refine your personal preferences to get the most personalized product recommendations as the researcher did in the demo section. You are also allowed to review any recommended printer showing in the result section.

The recommended result will be very similar as the following picture.



Once you have found the most appropriate printer, please move to the following questions.

Please answer the following questions based on your feelings/attitudes about your previous experiences and frequencies of utilizing this type of online recommendation system (prior to performing the above task)

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