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Assessing the Impact of Recommendation Agents on On-line Consumer Unplanned Purchase Behavior

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Abstract

Recommendation agents have been used by many Internet businesses such as Amazon and Netflix. However, few have studied how consumer behavior is affected by recommendation agents that guide online consumers based on their current shopping behavior. Fewer still have examined the role which recommendation agents play in influencing impulse purchasing decisions online. This study develops a theoretical model which illustrates the impact of recommendation agents on online consumer behavior. The model is tested through an online shopping simulation which uses a collaborative filtering based product recommendation agent. Particular attention is paid to the effects of a recommendation agent on consumer behavior along the dimensions of product promotion effectiveness, product search effectiveness, satisfaction with the website, and unplanned purchases. Results suggest that the theoretical model provides insights into the impact of a recommendation agent on online consumer behavior and offers suggestions for implementing such systems.

Keywords: recommendation agent, consumer purchase, unplanned purchase, online consumer behavior, consumer e-commerce, user satisfaction

Assessing the Impact of Recommendation Agents on On-Line Consumer Purchase Behavior

Introduction

Business to Consumer (B2C) electronic commerce has become a large and important segment of the new digital economy over the last ten years. Online retailers like Amazon.com and service providers like Netflix.com have come to dominate their respective market segments online. One of the tools used on the websites of these online powerhouses is recommendation agents. These agents are utilized to provide the customer with a customized online shopping experience. Many researchers have speculated that Recommendation Agents (RA) provide a great opportunity for online merchants to influence customers' behavior (Gretzel & Fesenmaier, 2007; Li, Myaeng & Kim, 2007; Senecal & Nantel, 2004; Swaminathan, 2003; Wang & Benbasat, 2007). The results of several studies have suggested different ways in which recommendation agents may influence online consumer behavior. Depending on the nature of the RA and its design objectives, the agent may persuade the customer that some product attributes are more important than others (Gretzel & Fesenmaier, 2007) or come away from their online shopping experience more satisfied with the outcomes (Felfernig & Gula, 2006).

A complementary thread of research from the marketing literature has examined the process by which consumers shop for and purchase goods and services. Several models describing this consumer buyer behavior have emerged over the years. Now that consumers are increasingly buying products online via the Internet, researchers and practitioners alike have become interested in how the technological aspects of online shopping affect consumer behavior. The point at which online shopping, the use of intelligent software agents and consumer buyer behavior theory come together is the primary focus of this study. The previous studies on these various aspects of web-based B2C e-commerce all have important theoretical implications for this study. They lay a theoretical groundwork that helps identify online buying process factors that may be important to measure the agent's impact. While several researchers have cited areas of consumer behavior theory where agents seem to logically fit into the purchasing process (Aggarwal & Vaidyanathan, 2003; Maes, Guttman, & Moukas, 1999; Häubl & Trifts, 2000; Schafer, Konstan, & Riedi, 1999) none have attempted to closely link or examine what impact agent usage has on the various phases of the consumer buyer behavior model. A few studies have examined the impact of intelligent software agents on the product selection and merchant selection processes, but little research has been done in other areas.

One very important unexamined research area involves assessing how these software agents affect consumers during the initial phase of the buying process, the moment when they realize that they want or need a particular product. There is little research which suggests how consumer behavior is affected by use of RAs that recommend specific products to online consumers based on their current shopping behavior. Most of the research on the use of RAs deals with the later stages in the purchase process where a consumer is trying to decide among a set of alternative products (Fitzsimons & Lehmann, 2004; Li, Myaeng, & Kim, 2007; Rowley, 2000; Senecal & Nantel, 2004; Vijayasarathy & Jones, 2000). Very few studies have examined the role of impulse purchasing in online consumer behavior, even though such purchasing has been shown to be a very large component of shopping behavior (Hausman, 2000; Peck & Childers, 2006). Fewer still have examined the role which the use of RAs plays in influencing satisfaction with website and impulse purchasing decisions online.

The objective of this research is to empirically test the impact of the use of RAs on online consumer purchase behavior regarding unplanned purchases on line, as well as consumer affective reaction to product promotion, product search, and satisfaction with the website. Needless to say, if the use of RAs can be shown to produce a significant positive impact on any of these commercially important variables, companies engaged in B2C electronic commerce should increase their efforts experimenting with this relatively new technology and implementing more effective RAs. Moreover, understanding the effects of intelligent web technologies on consumers' online behaviors is also essential to the success of any web-based businesses, as the interaction between firms and consumers through web technologies has already become a fundamental element of the new digital economy.

To accomplish its objectives, the study closely examines the influence of the use of an RA on product promotion effectiveness, product search effectiveness, customer satisfaction with the website, and unplanned or impulse purchases. To close some of the specific knowledge gaps discussed earlier, regarding the use of agent technology in e-commerce and its effects on consumers, we created a simulated online shopping environment in which some data can be collected to empirically study the impact of the use of RAs in an online retail environment. The results of this study are likely to aid online businesses in determining the most effective strategies for reaching and serving their customer base, as well as maximizing revenue from online sales. The next section presents the theoretical model, followed by the research methodology of the study. The subsequent sections present the results of our hypotheses and the implications of the study results. Finally, the contributions and limitations of the study are discussed, and future research opportunities are also presented.

Theoretical Framework

In building the theoretical framework for this study, we utilize previous research regarding consumer behavior theory, impulse purchasing behavior, consumer satisfaction, and agent usage in e-commerce. Figure 1 shows the theoretical model of this study, and the graphic model is followed by a detailed explanation of its components and relationships.

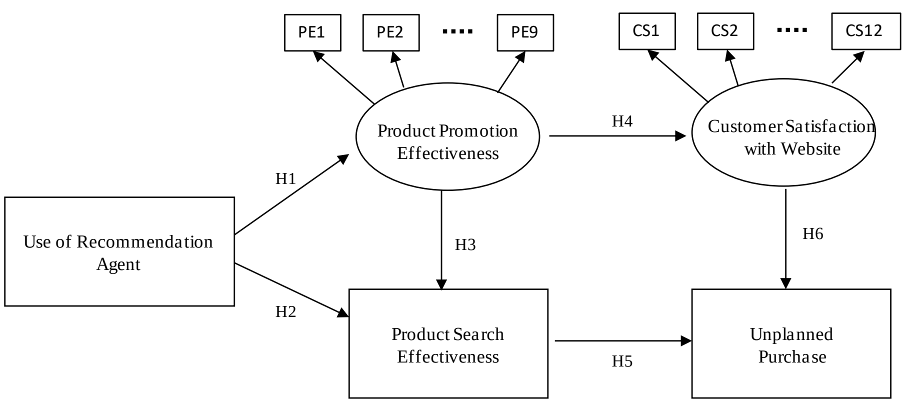

Figure 1 – The Theoretical Model

Product Promotion Effectiveness deals with the ability of the RA to recommend the product, its ability to attract the participant's attention to the specific product and developing interest in the recommended products. Online retailers may simply promote products and special deals to their customers without using a recommendation agent. However, general product promotions without some intelligent decision making as to what product the customer may be interested in will be of limited success. He et al. (2003) notes that, "shoppers with similar tastes and preferences are likely to buy similar products". Based on this finding, He et al. (2003) suggests that using collaborative filtering techniques to recommend a product that one consumer found attractive to another consumer who has similar tastes to the first, is an effective technique for increasing sales. Häubl and Trifts (2000) also found that use of RAs improved consumers' confidence in their purchase decisions, increased the quality of the set of products the consumers considered purchasing, and improved the quality of purchase decisions. The findings of these researchers support the assertion that the techniques used to make the recommendations are likely to be effective and that they can have a positive influence on consumer behavior. It is also reasonable to believe that if an RA is used to select which products to suggest to the customer, this guidance will enhance or improve the effectiveness of RA promotions by making them more attractive to the targeted individual shopper. Based on this discussion, we propose:

Hypothesis 1: The *use of an RA* is positively related to *Product Promotion Effectiveness*.

Since RAs present lists of recommendations ranked by predicted attractiveness to consumers, consumers who use RAs are expected to search through and acquire detailed information on fewer alternatives compared to those who shop without use of RAs, resulting in a smaller search set. Consequently, the use of RAs is expected to increase the product search effectiveness by reducing the total size of alternative sets as well as the size of search sets and the consideration set (Häubl & Murray, 2003; Häubl & Trifts, 2000; Xiao & Benbasat, 2007). Several studies showed that the use of RAs reduced the total number of products study participants examined (Dellaert & Häubl, 2005; Moore & Punj, 2001), and that the use of RAs reduced the number of products about which detailed information was sought (Häubl & Trifts, 2000). Swaminathan (2003) stated that use of an RA had a great impact on reducing the amount of search, and Diehl (2003) reported that use of an RA affects the amount of search. Last, Häubl and Murray (2006) reported that the presence of an RA reduces search effort which is measured by a number of alternatives examined. Nevertheless, the reader is reminded that while the discussion above provides a strong motivation for our next proposed hypothesis, for the purposes of this study we have defined Search Effectiveness as the ratio between the number of products purchased and the number of products examined. Thus, Search Effectiveness is calculated by the number of movies purchased divided by the total number of movies examined. Based on the above discussion, we propose:

Hypothesis 2: The *use of an RA* is positively related to *Search Effectiveness*.

After the consumer has been exposed to a product recommendation, by either a recommendation agent or some other means, they will respond based on their perception of the recommendation. They may decide to examine the recommended item more closely if the item is attractive enough to them to successfully draw their attention and entice them to act, or they may simply ignore the product recommendation altogether. Prior studies have proposed that recommendation agents provide more relevant product information and in turn improve customer decision quality (Hostler, Yoon, & Guimaraes, 2005; Pereira, 2000). Given the context where customers are seeking information on specific products for purchase, the more relevant the information available to the customer, the better chance that the customer would find the products attractive for purchase consideration. Thus, we propose:

Hypothesis 3: *Product Promotion Effectiveness* is positively related to *Product Search Effectiveness.*

The outcomes from an appropriate and meaningful product recommendation may vary widely based on circumstances. Consumers may find the product suggestions useful and desire to buy the product, but there may be other constraints that prevent them from doing so. It is also possible that a shopper may simply decide to defer a purchase of a recommended product to a later date for many extraneous reasons. The individual does not actually need to purchase a product to indicate his/her satisfaction with the product suggestions and recommendations provided by an e-commerce website. On the other hand, whenever customers find the RA product suggestions helpful and useful, that is likely to increase their level of satisfaction with the website. The research relevant to this issue provides some support for this assertion. Shafer et al. (1999) found that websites that make recommendations perceived as helpful and useful by customers will increase their level of satisfaction with that site. Felfernig and Gula (2006) proposed that participants in their study who used a recommendation agent were more satisfied with the decision making process at the website. Thus, we propose:

Hypothesis 4: RA *Product Promotion Effectiveness* is positively related to *Consumers' Satisfaction* with the merchant's website.

The topic of unplanned purchases or impulse buying has long been important to researchers and practitioners interested in consumer behavior. A very wide variety of possible factors related to unplanned purchases have been studied. The psychological and shopping environmental determinant factors have been addressed by Park and Lennon (2006). Jeffrey and Hodge (2007) found that unplanned purchases increase with the dollar amount spent on other items. Individual consumer tendency and gender have shown to increase the likelihood of unplanned purchases (Shoham & Brecic, 2003; Coley & Burgess, 2003; Verplanken & Herabadi, 2001). Mai et al. (2003) found that individualism, age, and income are related to unplanned purchases among Vietnamese consumers. In the domain of e-commerce, specifically, there seems to be little research regarding impulse buying. Hausman (2000) found that information overload plays an important role. Thus, one may surmise that information systems such as a recommender agent may reduce information overload and unplanned purchases. On the other hand, Bressolles et al. (2007) found a direct relationship between website quality and unplanned purchases.

During the product search process the consumer is being exposed to products that they had not originally been shopping for, and any additional items sold as a result of the exposure to the product line constitutes unplanned purchases or impulse buying. Each time a customer clicks on a link to the detailed information about a particular product, the act of clicking on that link is an indication that the subject wants to examine the product more closely. As discussed above, prior research on unplanned purchases has examined many other factors that influence desire for goods. By facilitating access to product information and effectively promoting the product, the use of an RA is likely to provide a powerful business benefit: unplanned purchases. Thus, we propose:

Hypothesis 5: *Product Search Effectiveness* is positively related to *Unplanned Purchases*.

In Rook's (1987) study of impulse purchasing behavior, forty-one percent of the participants reported feeling satisfied with their impulse purchases, indirectly identifying a positive relationship between customer satisfaction with the website and unplanned purchases. Another survey showed that the website design influences consumer satisfaction with it; that, in turn, influences impulse purchases more than the product price (User Interface Engineering, 2008). Dabholkar and Sheng (2008) reported that the consumer use of recommendation agents strongly influenced purchase intentions through the mediating effects of satisfaction. The literature indicates that the consumer satisfaction with the merchant website may affect the unplanned purchase. Consequently, we hypothesize:

Hypothesis 6: *Consumer Satisfaction* with the merchant site is positively related to *Unplanned Purchases*.

Research Method

Experimental Design

To test the hypotheses, we conducted a lab-controlled, between-subject experiment. Subjects were randomly assigned to either the control or treatment group. Both groups were provided with nearly identical instructions except different web addresses provided for accessing the experimental website. The product database for the experimental website, as well as the film ratings set used by the collaborative filtering recommendation agent, is from the MovieLens database constructed by the GroupLens Research Group at the University of Minnesota. While the entire film set (3883 films) in the database was used as a product database, movie recommendations were made from the top fifteen hundred (1500) most frequently rated films in the MovieLens dataset.

Table 1 shows the activity sequence of the experiment. Participants first filled out their pre-test questionnaire which included questions on relevant demographic data, as well as information on the subjects' level of online shopping experience. The pre-test questionnaire also listed thirty films which were randomly selected from the 1500 most frequently rated films for rating. Both groups rated the films to keep their experiences as similar as possible and to keep the control group from completing the experiment in a significantly shorter amount of time than the treatment group. However, only the film ratings of each treatment group subject were analyzed by a collaborative filtering recommendation agent to identify his/her unique reference user from the MovieLens dataset for each subject. The recommendation agent then used the current subject's reference user to select other films the subject might also enjoy based on a Pearson's correlation.

Subjects were then provided with a shopping scenario and asked to complete the shopping task in the experimental e-commerce website. The shopping scenario asked the participants to shop for home videos from an online movie merchant's website. The premise of the shopping scenario was that the subject had just completed installing a new home theater system in their home, and they wanted to purchase some new movies to watch on their new theater system. Before actually beginning to shop online for movies, the participants were asked to spend a few moments considering what movies they might want to add to their video collection and to make a list of the films they planned to purchase. Subjects were provided with an online form in which to list the movies they were thinking of purchasing. They were given no guidelines as to how many movies to purchase so as not to impede any impulse purchase decisions they might make while using the online shopping website. This thought process was a surrogate for a consumer's pre-purchase planning.

By giving some consideration to the purchase before shopping, and making a note of the study participant's purchase intentions, we were able to compare planned purchase intentions and impulse purchase outcomes. The control group completed the shopping simulation without the recommendation agent enabled in the experimental website. For the control group, five movies were randomly selected from the same 1500 films the agent made recommendations from and were displayed on each page throughout the experimental website. The five movies selected for the control group represented possible films an online merchant's marketing staff might select for promotion to customers. Meanwhile, the treatment group completed the shopping task on a different version of the same experimental website. The version of the website used by the treatment group included a recommendation agent to make product recommendations based on the subjects' film ratings and current shopping behavior. Each time a subject in the treatment group added a movie to their virtual shopping cart or viewed the product details for a movie, the recommendation agent selected five movies to recommend using a collaborative filtering technique. If the reference user rated a movie with a four or five (on a five point scale), and the movie was in the same genre family as the film the study participant was looking at, the agent would select that movie as a recommendation. To be in the same genre family, two films needed to be in one or more of the same genre categories because films were often categorized as belonging to more than one genre. For instance, one film might be categorized as being in the action, war, and sci-fi genres.

To be in the same "genre family" a second film might be categorized in the action and war genres. So while the two films were not exact matches based on genre, we considered them to be in the same genre family.

Upon completion of the online shopping simulation, subjects were asked to complete an online survey questionnaire. The final online questionnaire was used to collect data on the subjects' impulse buying tendency, the effectiveness of the product promotion, and their satisfaction with the website.

The website for the experiment was constructed using Apache web server, MySQL database server, and PHP scripting. The experimental website was instrumented to collect relevant data about the number of items that the subjects examined, as well as storing the final contents of each subjects' virtual shopping cart.

Steps	Activities	Objectives (*Constructs measured in italics*)
1. Pre-test	• Demographic Questions • Online Shopping Experience Questions	• Homogeneity of two groups tested
	• Movie Rating	• Reference User(s) identified
2. Simulated Shopping	• Listing movies that a subject plans to purchase	• Planned purchase
	• Searching and adding movies in a shopping cart	• *Production Search Effectiveness* • *Unplanned Purchase*
3. Post-test	• Posttest questionnaire	• *Product Promotion Effectiveness* • *Customer Satisfaction with website*

Table 1: Activity Sequence of Experiment

Measurement of Variables

1. Product Promotion Effectiveness

This variable addresses the ability of the RA recommendations to attract the participant's attention and develop interest in the recommended products. The construct was measured using a scale adapted from Nysveen and Breivik (2005). The scale includes nine items measured using 7 point Likert scales (1 for strongly disagree and 7 for strongly agree). The scale items ask the participant to rate their level of agreement with nine items related to their perception of the product suggestions provided by the experimental website. The statements relate to the subject's attitude towards the recommendations, their attitude towards the actual movies that were recommended to them, as well as the degree to which the recommendations helped them decide what movies to buy. First, a factor analysis was performed to determine if all the items in the scale loaded onto a single factor. All items had high loading with the smallest factor loading of 0.57. They led to a single-factor solution with an explained variance of 67.5% and the eigenvalue of 6.07. In addition to the factor analysis, a Cronbach's alpha score was computed for the scale to test the scale's internal consistency. The Cronbach's alpha for *Product Promotion Effectiveness* is 0.937, indicating that the scale is very reliable (Nunnally, 1978).

2. Product Search Effectiveness

The search effectiveness would depend on the extent to which the search mechanisms yield the product that the customer wants. Ideally, search effectiveness would depend on the "goodness" of the RA's logic. The number of alternatives searched alone is not a good measure for search effectiveness since the number of alternatives searched may be low because the search does not yield good results and leaves the consumer frustrated. In this study S*earch Effectiveness* refers to the ratio between the number of products purchased and the number of products examined. This was objectively measured by the experimental website. Each time a subject clicked on a link to the detailed information about a movie, the experimental website captured that activity. The act of clicking on a movie's detail information link was used as an indication that the subject was engaged in examining the product information for that product more closely. The experimental website used for the shopping simulation recorded the movie title and a date/time stamp as well as the participant's PHP session ID each time a subject clicked on a product link during the shopping session. At the conclusion of the experiment, the total number of movies examined during each participant's shopping session (identified by its unique PHP session ID) was determined. Search Effectiveness is calculated by the number of movies purchased divided by the total number of movies examined. Given that the only difference between the websites used by the treatment and control groups is the recommendation agent, any significant difference in the Search Effectiveness of the website between the two groups must be attributed to the presence or absence of the recommendation agent in the website's design and operation.

3. Customer Satisfaction with the Website

This measure was adapted from the American Customer Satisfaction Index (ACSI) used for measuring users' e-commerce website satisfaction. It includes twelve items which cover such areas as the information content of the website, the usability of the website, and the participant's level of satisfaction with the outcomes of the shopping process (i.e. were they satisfied with the products they bought and did they enjoy the shopping experience). There are twelve statements included in the scale with which the participants were asked to indicate their level of agreement using seven point Likert scales. A factor analysis was performed to test the unidimenstionality of twelve items, and the internal consistency was also tested. All items had high loading with the smallest factor loading of 0.57. They led to a single-factor solution with an explained variance of 67.5% and the eigenvalue of 7.03. The Cronbach's alpha for Customer Satisfaction with the Website is 0.942, indicating that the scale is very reliable (Nunnally, 1978).

4. Unplanned Purchases

This variable was measured using data captured prior to and during the shopping simulation. Before beginning the actual shopping simulation portion of the experiment, participants were asked to provide a list of movies they thought they might purchase during their shopping session. This list constitutes planned purchases. A number of unplanned purchases were determined by subtracting the movies in the category of planned purchases from the list of movies in their virtual shopping cart at the end of their shopping session. After movie titles selected as "planned purchases" were removed from the shopping cart, the remaining movies were considered "unplanned purchases." The movies in the shopping cart are not actual purchases but show a customer's intention to purchase. The theory of reasoned action (TRA) suggests that individual behavior is determined by his/her intentions to perform the behavior (Fishbein & Ajzen, 1975). Based on TRA, this study uses a customer's intention to make unplanned purchases to measure his/her unplanned purchases.

Data Analyses and Results

Data was collected from 251 undergraduate business students at a mid-Atlantic private liberal arts college. Students represent a good target population for this study because they are relatively similar in terms of computer literacy and familiarity with B2C e-commerce. They are also very familiar with the general selection process for movies and are strong consumers of such products. The results from this study are clearly generalizable to the population at large engaged in this area of commerce.

The students were separated into two groups: 134 subjects in the treatment group, and 117 subjects in the control group. Study participants were randomly assigned to either the treatment or control group. Both the control group and the treatment group receive recommendations. The recommendations for the control group are chosen randomly from the list of available movies, whereas those for the treatment group are generated by the collaborative filtering recommendation algorithm. The collaborative filtering recommendation algorithm analyzes the movies that a particular user examines and uses that information to recommend similar movies that his/her reference user from the MovieLens data set rated highly. Thus the RA is recommending the movies that a user has more potential interest in. The ages of the participants ranged from seventeen to fifty seven, 62% of the subjects were male (156) and 38% were female (95). Table 2 below provides a summary of the study population.

Group	**N (Total)**	**N (Males)**	**N (Females)**	**Mean Age**	**Mean Years Work Exp.**
Treatment	134	88	46	22.53	6.7
Control	117	68	49	22.51	6.5
Total	251	156	95	22.52	6.6

Table 2: Subjects Demographics

Two tailed independent sample T tests were performed to test for differences between the control group and the treatment group for all thirty two pretest questionnaire survey items. The pretest results show that homogeneity of variance between the treatment and control groups held for all thirty two items. There were no significant differences between the two groups regarding their experience with personal computers, knowledge of Internet usage and on-line shopping on the Internet at the 0.05 level of significance. **The descriptive statistics of the four main study variables are shown on Table 3. The different number of observations for the various groups is due to missing data.**

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			.	**Control Group**	**Treatment Group**

Variables	N	Mean	STD	N	Mean	STD	N	Mean	STD
Product promotion effectiveness	244	3.92	1.37	114	3.19	1.30	130	4.56	1.08
Product Search Effectiveness	219	1.12	0.84	103	0.85	0.33	116	1.36	1.06
Customer Satisfaction with website	244	4.45	1.25	114	4.18	1.32	130	4.69	1.13
Unplanned Purchase	237	3.25	2.97	105	3.12	3.02	132	3.36	2.94

Table 3: Descriptive Statistics of Study Variables

Model Testing

As shown in Figure 1, the model involves a series of interrelated variables. We used structural equation modeling (SEM) to test our hypotheses. Statistical tools used to analyze the data include SPSS and AMOS 18. First, a basic analysis of the collected data, including test for item normality, means, standard deviations, and outliers, was performed in SPSS. The test yielded acceptable results. Then the full structural model was tested in AMOS. SEM consists of two components: a *measurement model* linking a set of observed variables to a usually smaller set of latent variables and a *structural model* linking the latent variables through a series of recursive and non-recursive relationships.

The Measurement Model and Its Validity/Reliability

Confirmatory factor analysis (CFA) corresponds to the measurement model of SEM. CFA using maximum likelihood estimation (MLE) was conducted to assess the validity of constructs. In this test, all latent variables were allowed to correlate with each other. The results of the CFA measurement model are presented in Table 4. The standardized regression weights can be interpreted as the correlation between the observed variable and the corresponding common factor. The values showed that all items loaded on their respective construct as expected. For example, PE5 (0.889) and CS8 (0.877) have the highest standardized factor loadings, and PE9 (0.478) and CS1 (0.518) have the lowest factor loadings. Critical ratios of these regression weights are all significant at 0.05 (>1.96) level. Since all factor loadings are significant, it provides support for convergent validity of the construct.

Model Path	Standardized Factor Loading	Critical Ratio
PE1 ←Product Promotion Effectiveness	0.850	(Fixed)
PE2 ←Product Promotion Effectiveness	0.813	14.959
PE3 ←Product Promotion Effectiveness	0.841	15.826
PE4 ←Product Promotion Effectiveness	0.794	14.398
PE5 ←Product Promotion Effectiveness	0.889	17.511
PE6 ←Product Promotion Effectiveness	0.875	17.015
PE7 ←Product Promotion Effectiveness	0.729	12.613
PE8 ←Product Promotion Effectiveness	0.783	14.085
PE9 ←Product Promotion Effectiveness	0.478	7.343
CS1 ←Customer Satisfaction with website	0.518	(Fixed)
CS2 ←Customer Satisfaction with website	0.638	6.983
CS3 ←Customer Satisfaction with website	0.758	7.665
CS4 ←Customer Satisfaction with website	0.767	7.713
CS5 ←Customer Satisfaction with website	0.792	7.832
CS6 ←Customer Satisfaction with website	0.625	6.899
CS7 ←Customer Satisfaction with website	0.863	8.144
CS8 ←Customer Satisfaction with website	0.877	8.203
CS9 ←Customer Satisfaction with website	0.876	8.197
CS10 ←Customer Satisfaction with website	0.639	6.988
CS11 ←Customer Satisfaction with website	0.750	7.625
CS12 ←Customer Satisfaction with website	0.871	8.216

Table 4: Measurement Model Results

Although the original test showed that all items appear to be good indicators of the latent variables, the model fit can be improved by reviewing the modification indices (MI). Large MI values indicated factor cross-loadings (i.e., a loading on more than one factor) and error covariances. A large error covariance can be triggered by a high degree of overlap in what two items are attempting to measure. For example, CS1 asked whether the information on the website is accurate, while CS2 asks whether the quality of information on the website is good.

Provided with information related both to model fit and to possible areas of model misspecification, the post hoc analyses yielded a Chi-square/ degree of freedom value of 1.975. It falls into the recommended range of 1 and 3 (Bentler, 1990). The model has a comparative fit index (CFI) value of 0.952, which is above the stringent cutoff threshold of 0.95 suggested by Hu and Bentler (1999). The root mean square error of approximation (RMSEA) has been recognized as one of the most informative criteria in covariance structure modeling. Our data yielded the RMSEA value of 0.068, which is within the acceptable range (less than 0.08) for good model fit (Browne & Cudek, 1993). These critical indices demonstrated good fit between the measurement model and the data.

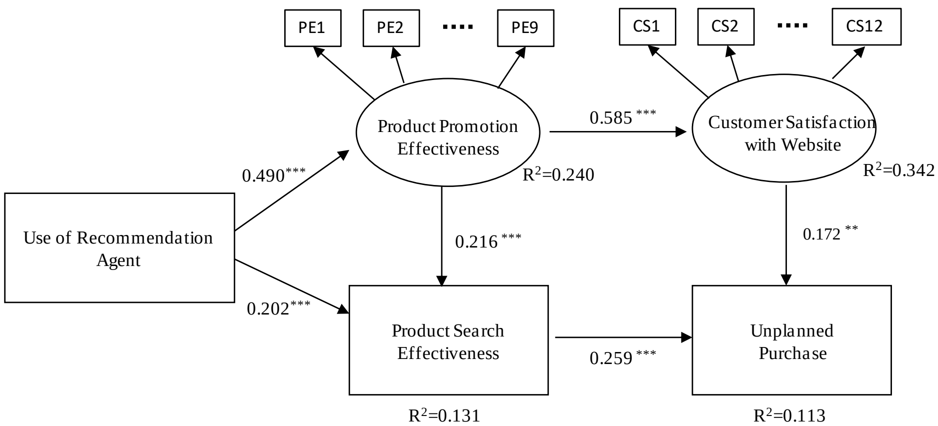
Further assessment of the measurement model was performed to examine discriminant validity and internal consistency. The correlation coefficient between the two constructs is 0.584. The correlations are less than the threshold value 0.80, suggesting discriminant validity (Bagozzi et al. 1991). Composite reliability is a measure of internal consistency of the construct. The reliabilities of the measurement items, along with the composite reliability of each construct are examined. The Cronbach's alpha values for composite reliability are 0.934 and 0.940, respectively. These values are greater than the recommended value 0.7 (Nunnally & Bernstein, 1994). This suggested that each of the scales is reliable. The internal consistency criteria are met.

Results from Testing the Structural Model

The structural model presented in Figure 1 was tested using AMOS to examine path significance levels. Table 5 summarizes the estimates of the structural model and the results are also presented graphically in Figure 2.

Model Path	Standardized Path Coefficient	Critical Ratio	P-value	Hypothesis
H1: Use of RA → Product Promotion Effectiveness	0.490	7.461	<.0.001	Supported
H2: Use of RA → Product Search Effectiveness	0.202	2.729	0.006	Supported
H3: Prod. Promo. Effective → Prod. Search Effectiveness	0.216	2.808	0.005	Supported
H4: Product Promo. Effective → Customer Satisfaction	0.585	6.038	<.0.001	Supported
H5: Prod. Search Effectiveness → Unplanned Purchase	0.259	3.944	<.0.001	Supported
H6: Customer Satisfaction → Unplanned Purchase	0.172	2.444	0.015	Supported

Table 5: Estimates of the Structural Equation Model and Hypothesized Path Testing



Note: ***p<0.01; **p<0.05; *p<0.10. All path coefficients are significant.
Chi-Square/df = 2.14, GFI = 0.84, CFI = 0.93, RMSEA = 0.073

Figure 2 – The Estimated Structural Equation Model

The overall measurement model provided an acceptable fit with Chi-square/degrees of freedom ratio = 2.14, which is within the recommended range between 1 and 3 (Bentler, 1990). The goodness-of-fit as measured by GFI is 0.84. The measurement model also produced a comparative fit index (CFI) value of 0.93, within the acceptable range (greater than 0.9 for a well-fitting model) proposed by Bentler (1990).

Other indexes of overall model fit are also recommended in the literature (Hoyle and Panter 1995). In our structured model, the normed fit index (NFI) is 0.871, and the Non-Normed Fit Index (NNFI) is 0.917. For a given set of data and variables, the goodness of fit of a more complex, highly parameterized model tends to be greater than for simpler models because of the loss of degrees of freedom of the complex model. Since NFI does not take into account model complexity, this measurement is not recommended. Instead, NNFI is often used to assess the overall model fit. In general, a value between 0.90 and 0.95 is acceptable, and above 0.95 is good.

The value of root mean square error of approximation (RMSEA) is 0.073, within the suggested range (less than 0.08) for good model fit (Browne & Cudek, 1993). The root mean square residual (RMR) in our model is 0.141. Usually the smaller the RMR, the better the model. RMR smaller than 0.05 indicates good fit.

Overall, all the fit statistics suggest acceptable fit consistent with guidelines provided in the literature. It provides support for satisfactory fit between the data and the proposed measurement model.

Results from Hypothesis Testing

All hypotheses are supported by data analysis. H1 suggested that the use of recommendation agent is positively related to product promotional effectiveness. This study provides strong empirical support for this relationship as the standardized path coefficient is 0.49 and $p<0.001$. Therefore, we can conclude that the use of recommendation agents can significantly enhance product promotional effectiveness.

H2 stated that the use of recommendation agent is positively related to search effectiveness. The path coefficient of 0.20 supported this relationship at the 0.01 significance level. This indicates that the use of recommendation agent can increase the e-commerce website's search ability.

H3 proposed a positive relationship between product promotion effectiveness and search effectiveness. The path coefficient is 0.22 and the *p* value suggested that the hypothesized relationship is significant at the 0.01 level. The results allow us to conclude that the use of the recommendation agent (directly), and more effective product promotions (indirectly), jointly have a positive impact on consumers' search effectiveness.

H4 posited that product promotion effectiveness is positively related to consumers' satisfaction. The path coefficient is 0.59 and the relationship was strongly supported at the 0.001 level. Product promotional effectiveness clearly leads to higher customer satisfaction.

H5 examined whether product search effectiveness is positively related to unplanned purchase consumer behavior. Our data also provided strong support for this relationship. The standardized path coefficient is 0.26 with *p* value less than 0.001.

Last, H6 predicted a positive relationship between customer satisfaction with the website and unplanned purchases. This is confirmed by the standardized path coefficient 0.172. The *p* value is 0.015, which supported the hypothesis at the 0.05 significance level.

Summary Results from Testing the Path Analytic Model

To sum up the results of the path model analysis, the direct-indirect-total effects among variables are presented in Table 6. Total, direct, and indirect effects have the same meaning they had in path analysis. If there is no path connecting two variables, the direct effect is zero. The indirect standardized effect is the product of the standardized path coefficients leading from one variable to the other. For example, the indirect standardized effect of the use of recommendation agent on customer satisfaction is 0.490×0.585=0.287. The total effects equal the sum of the direct and indirect effects. In terms of the relative power, the comparison of path coefficients and the total effects show that the impact of recommendation agent on customer satisfaction is the highest. This is primarily due to more effective product promotion through recommendation agent. Moreover, the effect of recommendation agent on product promotion effectiveness is higher than its impact on product search effectiveness. Eventually, several factors including customer satisfaction, product promotion and search effectiveness contribute to unplanned purchase.

	Direct Effect	**Indirect Effect**	**Total Effect**
Use of RA →Product Promotion Effectiveness	0.490		0.490
Use of RA →Product Search Effectiveness	0.202	0.106	0.308
Use of RA → Customer Satisfaction		0.287	0.287
Use of RA → Unplanned Purchase		0.129	0.129
Product Promotion Effectiveness → Customer Satisfaction	0.585		0.585
Product Promotion Effectiveness → Search Effectiveness	0.216		0.216
Product Promotion Effectiveness → Unplanned Purchase		0.157	0.157
Product Search Effectiveness → Unplanned Purchase	0.259		0.259
Customer Satisfaction → Unplanned Purchase	0.172		0.172

Squared multiple correlations (R^2) in the structural model: Promotion effectiveness (0.240), Product search effectiveness (0.131), Customer satisfaction (0.342), Unplanned purchase (0.113).

Table 6: Standardized Direct-Indirect-Total Effects Between Variables

In the path analysis of our structured model, there are two types of relationships between variables. If two variables are directly connected with a path link indicating a causal relationship (e.g., Use of RA → Product Search Effectiveness), we call it direct effect. If there are more than one path links between the two variables, i.e., the two variables affect each other through other variables (e.g., Use of RA → Product Promotion Effectiveness → Product Search Effectiveness), we call it indirect effect.

The standardized direct effect is the standardized path coefficient between the two variables. The standardized indirect effect is the product of the standardized path coefficients leading from one variable to the other. The total effects equal the sum of the direct and indirect effects. For example, the direct effect of the use of recommendation agent on product search effectiveness is 0.202. The indirect effect is $0.490 \times 0.216 = 0.106$. The total effect of Use of Recommendation Agent on Search Effectiveness is $0.202+0.106=0.308$.

Squared multiple correlations (R^2) for all endogenous variables were reported at the foot of Table 6 to check the effectiveness of the proposed model. The results indicate that 24% of the product promotion effectiveness' total variance is explained by the use of recommendation agent, while 13.1% of the product search effectiveness' total variance is explained by the use of recommendation agent. Although both hypotheses are supported, our results indicate that the use of recommendation agent has higher effect on product promotion effectiveness than search effectiveness. Further, 34.2% of customer satisfaction's total variance is explained by the use of recommendation agent and promotion effectiveness. 11.3% of unplanned purchase's total variance is explained by promotion effectiveness, search effectiveness, and customer satisfaction. Considering the limited number of variables involved, the proposed structural model is effective.

Overall, our results highlight the importance of using recommendation agent to positively influence online consumer purchase behavior. It is interesting to note that the major effect of recommendation agent is more effective product promotion, which leads to better customer satisfaction. In addition, product search effectiveness can be increased, which eventually contributes to more unplanned purchases. Our analysis indicates the business value of using recommendation agent on e-commerce sites. Successful implementation of recommendation agents can lead to both implicit (e.g., customer satisfaction) and explicit (e.g., profitability gained by unplanned purchase) benefits.

Conclusions, Recommendations, and Opportunities for Further Research

This study developed a theoretical model which explains the relationships between the various constructs in the online shopping process. Our model shows clear relationships between recommendation agent use and product promotion effectiveness, product search effectiveness, customer satisfaction with the website, and unplanned purchases. Our findings increase the level of knowledge available about the relationship between intelligent agent use in e-commerce and consumer buyer behavior theory. We can now say that in general using a recommendation agent to aid customer e-commerce shopping has a clearly positive impact. We can also state that the use of the recommender agent enhances online consumers' satisfaction with the website as a whole, provides a vehicle for better product promotion, a more effective product search process, and increases consumers' unplanned purchases.

Recommendations to Marketers

Specifically, this study's results indicate that recommendation agents reduce the extent of product search by providing quick access to relevant information focused on the items being sought and more effective promotion of selected products. Such product promotion can, in turn, increase the level of customer satisfaction with the website. Further, the knowledge gained here provides a basis for projecting the potential of intelligent agent technology to a much broader business arena. The use of Internet agents can be useful for individual shoppers at home or at work for saving time and improving shopping decision quality. As Internet shopping proliferates and the number of purchasing decisions per user increases, the use of decision aids such as this RA becomes increasingly necessary. It is important for business marketers considering a web-based e-commerce sales strategy to understand the potential positive and negative implications intelligent agent technology has in the online shopping space. Those organizations that understand the importance of this new technology and its business impact are then better positioned to compete in the world market. In the future it may not be enough just to provide consumers with a large selection of products to browse from the comfort of their homes. Websites implementing new effective ways to leverage the available technology to assist consumers through the online shopping experience are likely to gain a distinctive advantage. Shopbots and other forms of intelligent shopping agents are likely to play an integral role in that evolutionary process. Besides learning about it themselves, it behooves e-commerce business marketers to assist consumers in learning about the potential and limitations of Internet Agents as decision support tools. Needless to say, the characteristics of specific agents must be well understood before such tools can gain widespread acceptance by the business community. Accomplishing this essential task is considered beyond the scope of this report but provides a strong invitation for practitioners and researchers to work together toward this important goal.

Recommendations to RA Developers and Implementers

While this study clearly showed great business benefits from the use of a recommender agent and provided numerous other insights, it also has revealed some technical/operational problems and limitations in the way the RA system was developed and implemented. Because of the necessity of the movie ratings from the MovieLens dataset which were needed by the recommendation agent to form product recommendations, we were limited as to which films could be included in the product database for the experimental website. The latest MovieLens dataset that was available was a few years old. This limitation meant that we could only use films in the product database that were a bit older. The problem is that many of the undergraduate students who participated in the study commented that new film releases that they would have been the most interested in purchasing were not included in the product database. Although they were all able to find older films that they had seen and were interested in purchasing, these films were not always at the very top of their "must have" list of movies on DVD. This limitation may or may not have had an effect on the number of unplanned purchases that they made. Because their "first choice" films were not available in the product database, they were somewhat forced to fall back to alternative choices which they may not have originally planned to purchase.

Also, the collaborative filtering approach used for the recommendation agent in the study has some limitations as well. The first is what is known as the "cold start" problem. The cold start problem occurs when the recommendation agent needs to make recommendations to a new user for whom it has no preference data. To address the cold start problem, the recommendation agent needs some way to either gather some initial preference data from the user, or use preference data from another user until some data can be collected about the new user's preferences. In our study, we chose to collect initial preference data from each subject by asking them to rate a set of movies. This approach provided some initial preference data for each user, but was not a perfect solution.

Study Limitations and Opportunity for Further Research

Future research studies could compare the impact of different types of recommendation agents on the buying process to see which type of recommendation agent seems to be the most effective. In addition, future research with the theoretical model developed for this study might also examine how changes in product characteristics affect the impact that recommendation systems have. How might that change when the product mix is made up entirely of more expensive items such as personal computers, televisions, or even cars?

While this study provided useful insights into the use of Internet agents as shopping tools, it has many limitations, which represent opportunities for further research on this important topic. There is need for the identification and assessment of other user performance variables, which may benefit from the use of intelligent agents. Another important study would be the identification and assessment of various agent characteristics, which may make them more useful for e-commerce. From a methodological viewpoint, the use of a larger sample size may allow for the identification and assessment of user characteristics, which may provide useful clues for the design and development of new agent systems. The research opportunities are endless and represent a very important component of making the Internet an important new area of economic activity.

Regardless of the questions asked, the answer always seems to be that the use of recommendation agents has great potential as a business tool. Perhaps by answering some of the questions presented here, we can begin to identify new opportunities to use recommendation agents to improve the way in which consumers may use online shopping to continue to enhance their lives and fulfill their needs with these powerful new tools. Although online shopping is not likely to ever completely replace our real world shopping excursions, it continues to hold great promise for the future. Its convenience and ability to provide vast amounts of information on product features and availability can be used by consumers to get the most from their shopping experience.

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APPENDIX A: Summary of Measures for Variables in this Study

Recommender Agent (RA): The main independent variable in this study. While the movie recommendations to the control group are chosen randomly from the total list of available movies, movie recommendations to the treatment group are generated by the collaborative filtering algorithm of the RA which analyzes the movies that a particular user examines and recommends the movies that users in a similar group have rated highly.

Measurement scale for Website Product Promotion Effectiveness (PE), from Nysveen and Breivik [23]

[PE1] The movie suggestions were helpful.
[PE2] The movie suggestions made the website better.
[PE3] The movie suggestions were relevant.
[PE4] I became interested in a movie after it was suggested by the website.
[PE5] I liked the movies suggested by the website.
[PE6] The website suggested the kinds of movies I like.
[PE7] The information in the movie suggestions was useful for deciding whether or not to buy the movie.
[PE8] I feel that the movie suggestions helped me decide what movies to buy.
[PE9] I only needed to see the movie suggestion to decide whether to buy the movie, I didn't need any additional information before deciding whether or not to buy the movie.

Search Effectiveness: Measured using data captured during (products examined) versus after the shopping simulation. It is the ratio between the number of products purchased and the number of products examined.

Unplanned Purchases: Measured using data captured prior (intended or planned purchases) versus after the shopping simulation. Unplanned purchases were determined by subtracting the planned to purchase moviess from the list of movies in their virtual shopping cart at the end of the simulation.

Measurement scale used for Customer Satisfaction (CS) with Website, from ACSI website survey

[CS1] The information on this website is accurate.
[CS2] The quality of information on this website is good.
[CS3] I was able to accomplish what I wanted to on this website.
[CS4] This website was well organized.
[CS5] I was able to find the information I wanted on this website.
[CS6] I was able to easily navigate this website.
[CS7] This website met my expectations.
[CS8] This website compares favorably to my idea of an ideal website.
[CS9] I enjoyed shopping on this website.
[CS10] I felt good about the movies I decided to purchase from this website.
[CS11] This website had a good selection of products to choose from.
[CS12] I feel this website provides a good shopping experience.