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Assessing the impact of recommender agents on on-line consumer unplanned purchase behavior

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ABSTRACT

Recommendation agents (RAs) have been used by many Internet businesses such as Amazon and Netflix. However, few authors have studied how consumer behavior is affected by those that make suggestions to online consumers based on their recent shopping behavior. Fewer still have examined the role that RAs play in influencing impulse purchasing decisions online. Our study developed a theoretical model to illustrate the impact of RAs on online consumer behavior. The model was tested through an online shopping simulation which used a collaborative filtering based product RA. Particular attention was paid to the effects of an RA on consumer behavior; we found that it increased promotion and product search effectiveness, user satisfaction with the website, and unplanned purchases. Results showed that our model provided insights into the impact of an RA on online consumer behavior and thus provided suggestions for implementing effective systems.

1. Introduction

B2C electronic commerce has become a large and important segment of the new digital economy. Online retailers like Amazon.com and service providers like Netflix.com have come to dominate their market segments online. One of the tools used on the websites of these online powerhouses is the recommendation agent (RA): it provides a customized online shopping experience. Many researchers have speculated that RAs provide an opportunity for online merchants to influence customers' behavior [8,14,24]. Several studies have suggested ways in which RAs may influence online consumer behavior [20,22]. Felfernig and Gula [6] proposed that RAs may persuade the customer that some product attributes are more important than others or make the consumer more satisfied with their online shopping experience.

A complementary stream of research from the marketing literature has examined the process by which consumers shop for and purchase goods and services. Several models describing consumer purchase behavior have emerged over the years. Now that consumers are buying products online via the Internet, researchers and practitioners 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 behavior theory come together was thus the primary focus of our study.

Previous studies have provided a theoretical foundation that helps identify online buying process factors important in measuring the RA's impact. While several researchers have identified areas of consumer behavior theory where RAs seem to logically fit into the purchasing process [1], none has attempted to link or examine the impact that RA usage has on the various phases of the consumer buying 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 area involves assessing how software agents affect consumers during the initial phase of the buying process; i.e., when they realize that they want a particular product. Most of the research deals with the later stages in the purchase process where a consumer is trying to decide which one of the set of alternatives to purchase [7]. Very few studies have examined the role of impulse purchasing, even though such activities have been shown to be a very large component of shopping behavior [19]. Fewer have examined the role of RAs in influencing satisfaction with website and impulse purchasing decisions.

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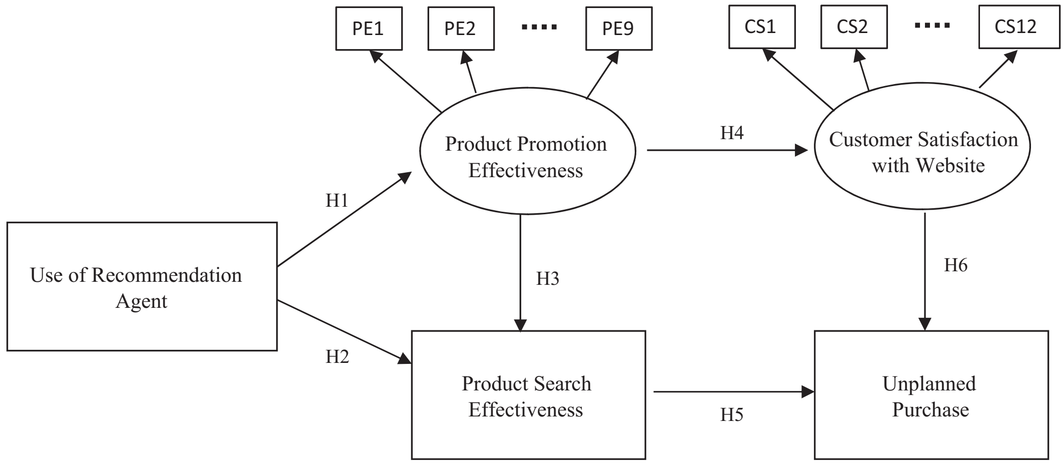

Fig. 1. The theoretical model.

The objective of our research was to test the impact of the use of RAs on online consumer purchase behavior of unplanned purchases on line, as well as consumer affective reaction to product promotion, product search, and satisfaction with the website. If the use of RAs can be shown to produce a significant positive impact on any of these commercially important variables, companies should increase their efforts to use more effective RAs. Moreover, understanding the effects of intelligent web technologies on consumers' online behavior is essential for the success of any web-based businesses.

To accomplish our objectives, we examined the influence of the use of an RA and created a simulated online shopping environment in which some data could be collected to study the impact of the use of RAs in an online retail environment.

2. Theoretical framework

In building our framework, we utilized previous results from consumer behavior theory, impulse purchasing behavior, consumer satisfaction, and agent usage in e-commerce. Fig. 1 shows our model.

Product promotion effectiveness deals with the ability of the RA to recommend products, its ability to attract the participant's attention to the products and develop interest in them. Online retailers may simply promote products and offer special deals to their customers without using an RA. However, general product promotions without some intelligent decision making as to what products the customer may be interested in will be of limited success. He et al. [11] suggested that, "shoppers with similar tastes and preferences are likely to buy similar products". Based on this, using collaborative filtering techniques to recommend a product that one consumer found attractive could be an effective technique for increasing sales. Such techniques are likely to be effective and can have a positive influence on consumer behavior. Therefore, we proposed:

Hypothesis 1. The use of an RA is positively related to product promotion effectiveness.

RAs have transformed the way in which consumers search for product information and make purchase decisions. Since they present lists of recommendations ranked by predicted attractiveness to consumers, customers who use RAs are expected to search through and acquire detailed information on fewer alternatives than those who shop without using RAs, resulting in a smaller search set. Consequently, the use of RAs is expected to increase product search effectiveness. Several studies have shown that the use of RAs reduced the total number of products that participants examined [9,25], and that the use of RAs reduced the number of products about which detailed information was sought. Lastly, Häubl and Murray [10] reported that the presence of an RA reduced search effort measured as the number of alternatives examined. We therefore proposed:

Hypothesis 2. The use of an RA is positively related to product search effectiveness.

After the consumer has been exposed to a product recommendation he or she will respond based on his or her perception of the recommendation. Prior studies have suggested that RAs provide more relevant product information and thus improve customer decision quality [12]. If the customers are seeking information on specific products, the more relevant the information, the better the chance that the customer will find the product attractive. Since the use of an RA signals the availability and status of related products, it can simplify the consumer's shopping by reducing search and decision costs. Through personalized product recommendation, RAs can also help fulfill consumers' need for information and exploration, resulting in improved product search effectiveness. Thus, we proposed:

Hypothesis 3. Product promotion effectiveness is positively related to product search effectiveness.

The outcomes from an appropriate and meaningful product recommendation may vary widely under different circumstances. Consumers may find the product suggestions useful and wish 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 to a later date. The individual does not actually need to purchase a product to indicate his or her satisfaction with the suggestions and recommendations. On the other hand, whenever customers find the RA product suggestions helpful, it is likely to increase their level of satisfaction with the website. Felfernig and Gula found that participants in their study who used an RA were more satisfied with the decision making process at the website. Thus, we proposed:

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 considered important by researchers and practitioners. A wide variety of possible factors have been studied. The psychological and shopping environmental determinant factors were addressed by Park and Lennon [18]. Jeffrey and Hodge [13] found

Table 1
Activity sequence of experiment.

Steps	Activities	Objectives (constructs measured in italics)
Pre-test	• Demographic questions • Online shopping experience questions • Movie rating	• Homogeneity of two groups tested • Reference user identified
Simulated shopping	• Listing movies that a subject plans to purchase • Searching and adding movies in a shopping cart	• Planned purchase • *Production search effectiveness* • *Unplanned purchase*
Post-test	• Posttest questionnaire	• *Product promotion effectiveness* • *Customer satisfaction with website*

that unplanned purchases increased with the dollar amount spent on other items. Individual consumer tendency and gender were also shown to increase the likelihood of unplanned purchases [3,21]. Mai et al. [15] found that individualism, age, and income were related to unplanned purchases among Vietnamese consumers. In the domain of e-commerce, there seems to have been little research on impulse buying. However, one can conjecture that decision aids may reduce information overload. Further, Bressolles et al. [2] found a direct relationship between website quality and unplanned purchases. Parboteeah et al. [17] also conducted a study of the relationship between impulsive purchases and the task-relevant cues of a web site, such as product descriptions and navigation aids. These studies did not however consider the effect of RA as a decision aid in impulse buying.

During the product search process the consumer is often exposed to products other than those they were originally seeking, and any additional items sold as a result of the exposure by an RA constitute an unplanned purchase. Each time a customer clicks on a link to obtain detailed information, the act is an indication that the customer wants to examine the product more closely. By facilitating access to product information and effectively promoting the product, the use of an RA may result in unplanned purchases. Thus, we proposed:

Hypothesis 5. Product search effectiveness is positively related to unplanned purchases.

Recent research has shown that the presentation of product information significantly affects consumers' satisfaction with electronic shopping. Both buying convenience and site design related to product offerings are considered to be among the dominating factors that help create a satisfactory customer experience [5,23]. Through RA technologies, the presentation of product information on the websites is thought to be more effective, making consumers aware of available products likely to be of interest to them. With less effort to acquire more relevant product information, quality and efficiency of decision making is likely to be improved. This, in turn, is likely to directly increase the consumer's satisfaction with the merchant's website, as well as substantially raise the likelihood and magnitude of impulsive purchases. Dabholkar and Sheng [4] reported that, with the aid of RAs, consumers' purchase intention was strongly influenced through the mediating effect of satisfaction. Consequently, we hypothesized:

Hypothesis 6. Consumer satisfaction with the merchant site is positively related to unplanned purchases.

3. Research method

3.1. Experimental design

The topic of our experiment was the online purchase of movie films from a merchant's website for home videos. The premise of the shopping scenario was that the subject had just completed installing a new home theater system and wanted to purchase some new movies. Using this scenario, we conducted a lab-controlled, between-subject experiment and tested hypotheses. Table 1 shows the activity sequence of the experiment.

First, subjects were randomly assigned to either a control or a treatment group. All participants filled out a pre-test questionnaire which elicited their demographic data, as well as information on their online shopping experience. The pre-test questionnaire also asked participants to rate thirty films which were randomly selected from the 1500 most frequently rated films in the MovieLens database created by the GroupLens Research Group (www.movielens.org). The RA then used these ratings to identify each subject's reference user for the treatment group.

Second, subjects were asked to complete the shopping task in the experimental e-commerce website. The participants were first asked to list the movies they considered purchasing. This thought process was a surrogate for a consumer's pre-purchase planning. The control group then completed the shopping simulation without the RA assistance. For the control group, five movies were randomly selected from the same 1500 films from which the RA made recommendations and were displayed on each page throughout the experimental website. Meanwhile, the treatment group completed the shopping task with the assistance of an RA which made product recommendations based on the identified reference user 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 RA selected five movies to recommend using a collaborative filtering technique.

Finally, upon completion of their online shopping, subjects were asked to complete a survey. This was designed to collect data on the subjects' impulse buying, 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 data about the number of items that the subjects examined, and storing the final content of each subjects' shopping cart.

3.2. Measurement of variables

3.2.1. Product promotion effectiveness

This construct was measured using a scale adapted from Nysveen and Breivik [16] which contains nine items asking participants to rate their level of agreement with statements about their perception of the product suggestions provided by the experimental website (see Appendix A). The statements were intended to measure the subjects' attitude towards the recommendations, their attitude towards the actual movies that were recommended to them, and the degree to which the recommendations helped them decide what movies to buy. The scale items were measured using seven-point Likert scales (1 for strongly disagree and 7 for strongly agree).

A factor analysis indicated that all the items in the scale loaded unambiguously into a single factor. The items had high factor loadings, with the smallest being 0.57. This single-factor solution explained 67.5% of the variance and produced an eigenvalue of 6.07. In addition to the factor analysis, a 0.937 Cronbach's alpha score was computed for the scale, indicating that its internal consistency was quite high.

3.2.2. Product search effectiveness

Search effectiveness depends on the extent to which the search mechanisms yield a product that the customer wants: this depends on the value of the RA's logic. The number of alternatives searched is not a good measure for this since the number of alternatives searched may be high because the search does not yield good results and makes the consumer repeat the search and become frustrated. In our study we defined search effectiveness as 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 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 every 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. Given that the only difference between the websites used by the treatment and control groups was the RA, any significant difference in the search effectiveness of the website between the two groups could be attributed to the presence or absence of the RA in the website's design and operation.

3.2.3. Customer satisfaction with the website

We adapted this measure from the American Customer Satisfaction Index (ACSI), which has been used for measuring users' e-commerce website satisfaction. It includes twelve items that 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., whether customers were satisfied with the products they bought, and whether they enjoyed the shopping experience). Appendix A shows the twelve statements used to indicate the participants level of agreement using seven-point Likert scales. A factor analysis was performed to test the unidimensionality of these twelve items. All items had high loadings 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 this scale was 0.942, indicating that the scale was very reliable.

3.2.4. Unplanned purchases

This was measured using data captured prior to and during the shopping simulation. Before beginning the 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 constituted their planned purchases. The number of unplanned purchases was determined by subtracting the movies in the category of planned purchases from the list of movies in the virtual shopping cart at the end of their shopping session. [Note that the movies in the shopping cart were not actual purchases but showed a customer's intention to purchase]. The theory of reasoned action (TRA) suggests that individual behavior would be determined by his/her intention to perform that behavior. We therefore used the customer's intention to make unplanned purchases as the measure of his/her unplanned purchases.

Table 2
Subjects demographics.

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

4. Data collection, analyses, and results

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

Participants were randomly assigned to either the treatment or control group. Both groups received recommendations: those for the control group were chosen randomly from the list of available movies, while those for the treatment group were generated by the RA, which analyzed the movies that a particular user examined and used them to recommend similar movies that matched his/her reference user from the MovieLens data set rated (the RA recommended movies of potential interest).

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 provides a summary of the study population.

Two-tailed independent sample *t*-tests were performed to assess differences between the control and the treatment groups for all thirty-two pretest questionnaire survey items. The results showed no significant difference between the groups on all thirty-two items. Most importantly, there were no significant differences between the two groups regarding their experience with personal computers, knowledge of Internet usage, and on-line shopping at the 0.05 significance level or better.

The descriptive statistics of the four main study variables are shown in Table 3. The different number of observations for the various groups was due to missing data. The four main variables that we studied had higher mean values for the experiment group than for the control group. This is an initial indication of support for our study's results.

4.1. Model testing

Our model involved a series of interrelated variables. We used SEM to test our hypotheses. Statistical tools used to analyze the

Table 3
Descriptive statistics of study variables.

Variables	*N*	Mean	STD	Control group			Treatment group		
				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 4
Measurement model results.

Model path	Standardized factor loading	Critical ratio
PE1 ← Product promotion effectiveness	0.85	(Fixed)
PE2 ← Product promotion effectiveness	0.81	15.0
PE3 ← Product promotion effectiveness	0.84	15.8
PE4 ← Product promotion effectiveness	0.79	14.4
PE5 ← Product promotion effectiveness	0.89	17.5
PE6 ← Product promotion effectiveness	0.88	17.0
PE7 ← Product promotion effectiveness	0.73	12.6
PE8 ← Product promotion effectiveness	0.78	14.1
PE9 ← Product promotion effectiveness	0.48	7.34
CS1 ← Customer satisfaction with website	0.52	(Fixed)
CS2 ← Customer satisfaction with website	0.64	6.98
CS3 ← Customer satisfaction with website	0.76	7.67
CS4 ← Customer satisfaction with website	0.77	7.71
CS5 ← Customer satisfaction with website	0.79	7.83
CS6 ← Customer satisfaction with website	0.63	6.90
CS7 ← Customer satisfaction with website	0.86	8.14
CS8 ← Customer satisfaction with website	0.88	8.20
CS9 ← Customer satisfaction with website	0.88	8.20
CS10 ← Customer satisfaction with website	0.64	6.99
CS11 ← Customer satisfaction with website	0.75	7.63
CS12 ← Customer satisfaction with website	0.87	8.22

data included SPSS and AMOS 18. First, a basic analysis of the collected data, involved a test for item normality, means, standard deviations, and outliers; it was performed using SPSS. This test yielded acceptable results. Then the full structural model was tested by using AMOS.

4.2. The measurement model and its validity/reliability

Confirmatory factor analysis (CFA) using maximum likelihood estimation (MLE) was conducted to assess the validity of our constructs. In this test, all latent variables were allowed to correlate with each other. The results are presented in Table 4. The standardized regression weights can be interpreted as the correlation between the observed variable and its corresponding common factor. The values showed that all items loaded on their respective construct as expected. Since all factor loadings were significant, this provided support for the convergent validity of the construct.

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

Further assessment of the measurement model was performed to examine discriminant validity and internal consistency. The correlation coefficient between the two constructs was 0.58. The correlations were less than the threshold value 0.80, suggesting good discriminant validity. The reliabilities of the measurement items, along with the composite reliability of each construct were examined. The Cronbach's alpha values for composite reliability are 0.93 and 0.94, respectively; these are greater than the recommended 0.7, indicating that both scales were reliable.

4.2.1. Results from testing the structural model

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

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

In our structured model, the normed fit index (NFI) was 0.87, and the Non-Normed Fit Index (NNFI) was 0.92. 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 generally recommended. Instead, NNFI is 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 RMSEA was 0.07, which is less than 0.08 suggesting good model fit. Overall, all the relevant statistics suggested an acceptable model fit consistent with normal guidelines, providing support for satisfactory match between the data and the proposed measurement model.

4.2.2. Results of hypothesis testing

All hypotheses were supported. H1 proposed that the use of an RA was positively related to product promotional effectiveness. Our study provided strong empirical support for this as the standardized path coefficient was 0.49 and $p < 0.001$. Therefore, we can conclude that the use of RAs can significantly enhance product promotional effectiveness.

H2 stated that the use of an RA was positively related to search effectiveness. The path coefficient of 0.20 supported this relationship at 0.01 significance level. This indicated that the use of an RA 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 was significant at the 0.01 level. The results allowed us to conclude that the use of the RA (directly), and more effective product promotions (indirectly), jointly had a positive impact on consumers' search effectiveness.

H4 posited that product promotion effectiveness was positively related to consumers' satisfaction. The path coefficient was 0.59 and the relationship was strongly supported at the 0.001 level.

Table 5
Estimates of the structural equation model and hypothesized path testing.

Model Path	Standardized path coefficient	Critical ratio	P-value	Hypothesis
H1: Use of RA → product promotion effectiveness	0.49	7.46	<.0.001	Supported
H2: Use of RA → product search effectiveness	0.20	2.73	0.01	Supported
H3: Prod. promo. effective → prod. search effectiveness	0.22	2.81	0.01	Supported
H4: Product promo. effective → customer satisfaction	0.59	6.04	<.0.001	Supported
H5: Prod. search effectiveness → unplanned purchase	0.26	3.94	<.0.001	Supported
H6: Customer satisfaction → unplanned purchase	0.17	2.44	0.02	Supported

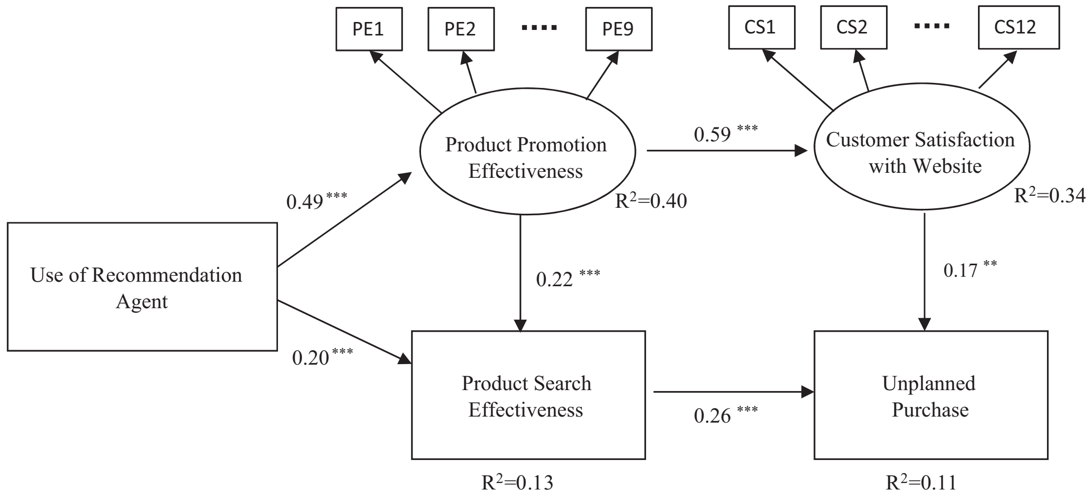

Fig. 2. The estimated structural equation model. *Note*: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$. All path coefficients are significant. Chi-square/df = 2.14, GFI = 0.84, CFI = 0.93, RMSEA = 0.07.

Product promotional effectiveness thus leads to higher customer satisfaction.

H5 examined whether product search effectiveness was 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.

Finally, H6 predicted a positive relationship between customer satisfaction with the website and unplanned purchases. This was confirmed by the standardized path coefficient of 0.17. The p value was 0.02, which supported the hypothesis at the 0.05 significance level.

4.2.3. Summary results from testing the path model

In the path analysis of our structured model, there were two types of relationships between variables. If they were directly connected by a path link indicating a causal relationship (e.g., use of RA → product search effectiveness), this we called a direct effect. If there was more than one path link 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 called it an indirect effect. The results of the path model analysis are presented in Table 6.

The standardized direct effect is the standardized path coefficient between the two variables. If there is no path connecting two variables, the direct effect is zero. The standardized indirect 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 an RA on customer satisfaction is $0.49 \times 0.59 = 0.29$. The total effect is the sum of the direct and indirect effects. The direct effect of the use of an RA on product search effectiveness was 0.20. The indirect effect was $0.49 \times 0.22 = 0.11$. The total effect of the use of an RA on search effectiveness was therefore $0.20 + 0.11 = 0.31$.

Examining the total effects we find that the impact of product promotion effectiveness on customer satisfaction is the highest (0.59). This is primarily due to more effective product promotion through an RA with a direct effect of 0.49. Moreover, the use of an RA had higher impact on product promotion effectiveness (0.49) than product search effectiveness (0.30). Eventually, several factors, including customer satisfaction, product promotion, and search effectiveness contribute to unplanned purchases.

Squared multiple correlations (R^2) for all endogenous variables were included to shown the effectiveness of our model. Apparently 24% of the product promotion effectiveness' total variance was explained by the use of an RA, while 13.1% of the product search effectiveness' total variance was similarly explained. Although both hypotheses were supported, our results indicated that the use of an RA had higher effect on product promotion effectiveness than search effectiveness. Further, 34.2% of customer satisfaction's total variance was explained by the use of an RA and by product promotion

Table 6
Standardized direct–indirect-total effects between variables.

	Direct effect	Indirect effect	Total effect
Use of RA → product promotion effectiveness	0.49		0.49
Use of RA → product search effectiveness	0.20	0.11	0.31
Use of RA → customer satisfaction		0.29	0.29
Use of RA → unplanned purchase		0.13	0.13
Product promotion effectiveness → customer satisfaction	0.59		0.59
Product promotion effectiveness → search effectiveness	0.22		0.22
Product promotion effectiveness → unplanned purchase		0.16	0.16
Product search effectiveness → unplanned purchase	0.26		0.26
Customer satisfaction → unplanned purchase	0.17		0.17

Squared multiple correlations (R^2) in the structural model: promotion effectiveness (0.24), product search effectiveness (0.13), customer satisfaction (0.34) and unplanned purchase (0.11).

effectiveness; 11.3% of unplanned purchase's total variance was explained by product promotion effectiveness, search effectiveness, and customer satisfaction. Considering the limited number of variables involved, our structural model was proved to be effective.

Overall, our results highlight the importance of using RAs to positively influence online consumers' purchase behavior. The major effect of using an RA is in more effective product promotion, which leads to greater customer satisfaction. In addition, product search effectiveness can be increased, which eventually contributes to more unplanned purchases.

5. Conclusions, recommendations, and limitations

We developed a theoretical model which explains the relationships between the various constructs in the online shopping process. Our model showed clear relationships between the use of an RA and product promotion effectiveness, product search effectiveness, customer satisfaction with the website, and unplanned purchases. We conclude that using an RA to aid customer online shopping can have a positive impact on businesses. Our results indicated that the use of the RA enhances online consumers' satisfaction with the website, provides a vehicle for better product promotion, a more effective product search process, and increases consumers' unplanned purchases.

5.1. Recommendations to marketers

Specifically, our results indicated that RAs represent an effective tool for B2C e-commerce. They can reduce the extent of product search by providing quick access to relevant information focused on the items being sought, and can provide more effective promotion of selected products. Such product promotion can increase the level of customer satisfaction with the website. Further, our results show the potential benefits of deploying intelligent agent technologies e-commerce. As Internet shopping proliferates and the number of purchasing decisions per user increases, the use of decision aids becomes increasingly necessary. It is important for business marketers to understand the potential positive and negative implications of RAs on online shopping. Those organizations that understand the importance of this new technology and its business impact are better positioned to compete in the network market.

Websites implementing effective technology to assist consumers through the online shopping experience are likely to gain a competitive advantage. Intelligent shopping agents are likely to play a major role in the design of new marketing strategies. Needless to say, the characteristics of specific intelligent agents must be well understood before such tools can gain widespread acceptance.

5.1.1. Recommendations to RA developers and Implementers

While our study clearly showed business benefits from the use of an RA and provided many managerial insights, it also has revealed some technical/operational problems and limitations. Because of the need for movie ratings to form product recommendations, we were limited to which films could be included in our database. The latest dataset that we could use was a few years old. Many of the students who participated commented that new film releases would have been more interesting but were not included. Although they were all able to find older films (some that they had seen and were interested in purchasing) these films were not at the top of their *must have* list. This limitation may or may not have had an effect on the number of unplanned purchases.

Also, the collaborative filtering approach used for the RA in our study had some limitations. First it had a *cold start* problem, which occurs when the RA needs to make recommendations to a new user for whom there is no preference data. To address this, the RA needs some way to either gather initial preference data or use preference data from another user until some data has been collected about the new user. In our study, we chose to collect initial preference data from each subject by asking them to rate a set of movies.

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

[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.

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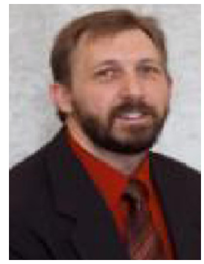

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