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Assessing the Moderating Effect of Consumer Product Knowledge and Online Shopping Experience on using Recommedation Agents for Customer Loyalty

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Assessing the moderating effect of consumer product knowledge and online shopping experience on using recommendation agents for customer loyalty

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Abstract

Social media technologies have greatly facilitated the creation of many types of user-generated information, e.g., product rating information can be used to generate preference-based recommendation. As a decision support tool, a Recommendation Agent (RA) has been widely adopted by many e-commerce websites. The impact of RAs on online shopping has been extensively examined in the IS literature. However, from Marketing and Social Media perspectives, the widely adopted cognitive–affect–conative–action framework of customer loyalty has not been tested in the presence of RAs. Moreover, there has been little research assessing the impact of increasing consumer knowledge about specific product domains on customer satisfaction and loyalty. Based on these important constructs, this study proposes and empirically tests a parsimonious model assessing the moderating effect of consumer product knowledge and online shopping experience on using RA for customer loyalty. The results show that consumer product knowledge relationship between RA's recommendations negatively impacts the recommendation quality and customer satisfaction, however, consumer online shopping experience does not have a significant effect on the relationship between customer satisfaction and customer loyalty. The results make a significant contribution to a better understanding of the constructs in our research model and provide evidence useful for the management of websites using RAs for product recommendations.

Keywords

Intelligent agents, Customer loyalty, Customer satisfaction with website, Customer value, Product knowledge, Online shopping experience

1. Introduction

In the last few years, user-generated information from ratings, tagging, and social networking support systems have allowed the development and improvement of preference-based, personalized recommender agent (RA) systems. In turn, as decision support tools, RAs have been widely adopted by many e-commerce websites and online applications. For example, Amazon and Netflix have used RAs extensively to support online consumers and these systems have demonstrated tremendous success as measured by increased sales and user satisfaction. Similarly, the social news site Digg uses history of likes and dislikes to deliver personalized recommendations to users, and Facebook's main recommender mechanism is its “Friend-of-Friend” algorithm. In general, the relatively high quality and relevant content provided by the RA systems are thought to significantly enhance the users' online experiences, which ultimately are expected to positively affect customer loyalty to the sites.

Customer loyalty has been widely recognized as a useful indicator for long-term business success. Previous studies have reported a powerful impact of customer loyalty on overall firm performance [40]. Rust, Zeithaml, and Lemon [52] reported a significant effect of customer loyalty on firm's performance, and that many companies consider customer loyalty an important source of competitive advantage. Further, Reinartz and Kumar [48] revealed a strong relationship between customer loyalty and a firm's profitability. Similarly, Fornell et al. [20] also discovered a strong positive relationship between customer loyalty and stock returns.

Due to the importance of customer loyalty for business success, academicians as well as practitioners have a keen interest in identifying the determinants of customer loyalty. The marketing literature has addressed various determinants of customer loyalty for over two decades [43], and the frequently reoccurring factors affecting customer loyalty include customer value, customer satisfaction, trust, and habit. A cognition–affect–conation–action conceptual framework with these determinants has been empirically validated in a variety of contexts, including B2C [58], B2B [32], mobile commerce [35], e-service [37], and internet-provider services [12]. Prior studies also have examined the impact of website design features on customer loyalty [13,39].

Originally, the concept underlying the use of RAs was to reduce customer information overload by recommending products that are likely to be of interest to them. The impact of RAs on online shopping has been extensively examined in the IS literature [6,27,28,45,61,63,64]. Prior studies have addressed how customers utilize RAs while shopping online, and what impact RA usage has on certain shopping behaviors. The nature of studies regarding RAs is diverse along several dimensions, and the experimental designs and shopping tasks used in the studies also vary greatly. However, from a marketing perspective, the widely adopted cognitive–affect–conative–action framework of customer loyalty has not yet been empirically tested in the context of RAs. This represents one of the main reasons for conducting this study. Another motivation for this study is that there has been little research assessing the effect of increasingly higher consumers' domain expertise on customer loyalty in the presence of RA usage. Because RA is designed to provide expert recommendations, a natural question is whether it is a substitute for consumers' domain expertise. If the answer to this question is positive to some extent, then consumers' evaluation for RA effectiveness may vary depending on consumers' expertise. Consequently, it may affect customer satisfaction and loyalty in the online shopping environment.

Drawing on the IS, Marketing and Social Psychology literature, we propose and empirically test a theoretical model examining the effects of an RA on customer loyalty and the moderating effect of product knowledge and online shopping experience on the model. In order to fill a gap in our collective knowledge about the use of RAs in e-commerce and its effects on customer loyalty, we created a simulated online shopping environment in which data can be collected to empirically study the impact of RA usage in an online retail environment and the moderating effect of consumers' expertise on the research model. Examining these variables is increasingly important as current RA practice seldom treats individuals differently based on user expertise. The next section addresses the theoretical foundations for this study. That is followed by sections discussing the research model; the research methodology; results; and summary, conclusions and recommendations for practitioners and researchers.

2. Theoretical background

In developing the theoretical framework for this study, we utilize several theories. The first theoretical basis is the more traditional theory of customer loyalty. Dick & Basu [15] presented the attitude-based framework of customer loyalty, which represents three phases – customer belief, affect, and intention – in the customer attitude structure. Oliver [43] extended this framework by adding the fourth phase of action, representing the progressive development of customer loyalty through

Oliver [43] argued that customers first become loyal in a cognitive sense based on prior knowledge or experience-based information regarding brand attributes. He refers to this stage as cognitive loyalty. Customers then become loyal in an affective sense. The second phase of affective loyalty represents the pleasure dimension of the customer satisfaction — affection toward a brand. Customers later become loyal in a conative manner, reflecting the customer's intention and desire to rebuy the brand. Customers become loyal finally in a behavioral manner — actual commitment to rebuying [43].

Based on the cognition–affect–behavior model, Lam et al. [32] proposed a conceptual framework that includes customer perceived value, customer satisfaction, switching costs, and customer loyalty in a B2B setting. The study results reveal that customer value has a positive impact on customer satisfaction, and customer satisfaction has a positive effect on customer loyalty. They also reported the significant mediating effect of customer satisfaction between customer value and customer loyalty. Numerous studies also proposed and empirically validated theoretical models drawn on this customer loyalty model in various contexts, including B2C [58], mobile commerce [35], e-service [37], and Internet Service Provider [12]. These studies also reported customer perceived value, customer satisfaction, trust and habit as the antecedents of customer loyalty.

The second theoretical basis of this study is the theory of human information processing that describes the limited cognitive capacity to process information [38,62]. The advance of e-commerce enables customers to access excessive volumes of information. Large amount of information is beneficial in the sense that more information is available for analysis to provide insight and alternatives. However, the effect of voluminous information is detrimental, causing information overload and challenging humans' cognitive abilities. The ability to utilize this information will require techniques that allow larger volumes of information to be analyzed. As a result, many different approaches have been proposed to assist with information overload including personalization, information filtering, and recommendation agents. RAs are particularly effective in addressing the information overload problem by providing assistance in a decision making context [34]; evaluating the potentially overwhelming number of alternatives and recommending items that are likely to be of interest to the customer. RAs are particularly useful for decision-makers where decisions must be made in a short time period and the effort required for interacting with the system is limited [51]. By supplying a recommendation based on some predictive elements relevant to the customer, RAs augment the customer's processing capacity for decision making process. Such RAs may have potential for influencing customer purchase action. It would be intriguing to analyze their effects on customer purchase behavior.

The theory of interpersonal similarity provides another theoretical basis for this study. Interpersonal similarity is viewed as a form of social distance in which an individual perceives similar persons as socially close to oneself than dissimilar ones [36]. As a form of social distance, interpersonal similarity, which is similar in attitudes, personality or background, develops a sense of closeness between individuals and thereby affects information processing about each other. Many studies have reported that higher levels of similarity lead to attraction [9]. A collaborative filtering recommendation agent recommends products to consumers with similar tastes and preferences [1]. He et al. [24] suggested that using collaborative filtering techniques to recommend a product that one consumer found attractive, to another consumer who has similar tastes to the former, is an effective technique for increasing sales. Drawing upon the similarity and attraction relationship that the interpersonal similarity theory posits, we argue that better recommendation leads to more customer satisfaction on the product recommended by the RA, which in turn positively affect customer loyalty.

Last, this study is also based on prior research of RA use in e-commerce. Previous studies have analyzed the effectiveness and impact of RAs on Internet e-commerce [63 for extensive review; 28, and 64 for more recent works]. These studies have examined RAs that make recommendations to aid the consumer in selecting a specific product within a product category (product brokering) or selecting an online merchant to purchase from (merchant brokering). The results suggest that the application of RAs in certain aspects of e-commerce can be effective in helping online consumers by providing additional decision support while shopping. Specific results include that RAs save decision time [27,61] and increase important factors such as decision effectiveness [6], decision quality [22,27,31], decision confidence [26], impulse purchase [28], sales [45], and loyalty [64]. Wang and Doong [62] analyzed the impact of customers' cognitive differences on the success of recommendation agents.

In this research, we position our study in the stream of collaborative filtering recommendation agents. Collaborative filtering (CF) is one of the most popular techniques for recommender systems. It relies on user-generated content such as ratings on items (e.g., movies, music, books, etc.) that the user has experienced, based on which the system identifies persons who have similar interests and then recommend to the user items that are preferred by these like-minded neighbors. This is in contrast with the content-based RA that generates recommendations based on product attributes (e.g., related authors, related titles of books) the consumer likes. More recently, hybrid models that combine collaborative and content filtering are proposed. These models typically rely on classification learning algorithms to induce rules that match content and users [1]. However, none of these popular RAs take into account users' prior product knowledge and online experience.

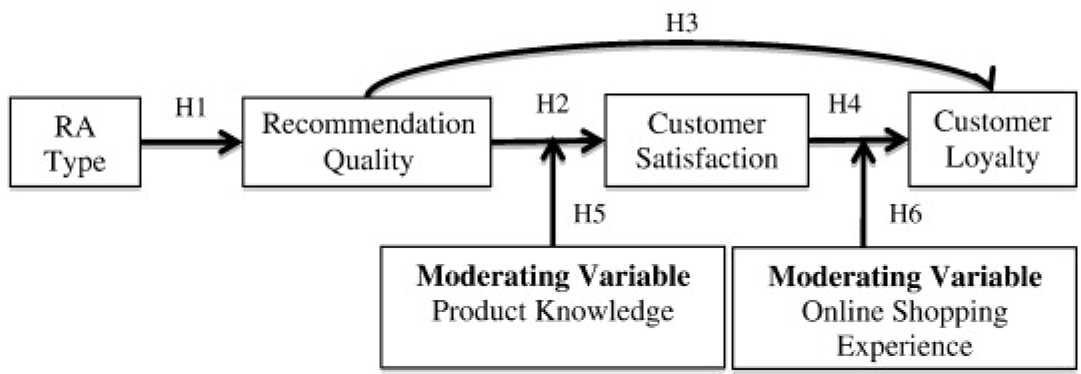
The collaborative filtering approach can be regarded as an implicit way to infer the preference relationship between users. In contrast to the relationships inferred by the system, social networks explicitly define relationship among users. For example, Last.fm is a music recommender website where users can establish friendship with others and join a group of users having similar music tastes. Therefore, social networks may contain information relevant to elicit user preferences. The infusion of social network into recommender systems is referred to as social recommender systems. One approach uses social subnetworks as rating neighborhoods, a technique called social filtering. However, the integration of the recommender systems with the social web yields mixed results. Groh and Ehmig [21] showed that social filtering is more effective than collaborative filtering in taste related domains. In comparison, Sinha and Swearingen [56] compared online recommender systems with social recommendation approaches and found that online RA recommended items were often “new” and “unexpected”, while the items recommended by friends mostly served as reminders of previously identified interests. Because the type of rated objects, the users of the system and their social connections, as well as the type of ratings all differ in different studies, it seems that field of application plays a prominent role for the performance of the social filtering approaches. In this study, we only focus on collaborative filtering implementation of the RA.

The marketing literature presents the cognitive–affect–conative–action framework of customer loyalty and empirically validates the research models drawn from the framework in various contexts. Further, the IS literature suggests that RAs can be effective in helping online consumers with product and merchant selection decisions through many empirical studies. However, few studies validate the cognitive–affect–conative–action framework of customer loyalty in the context of recommendation agents. Moreover, there has been little research that assesses the impact of consumer expertise on the customer loyalty framework. Our theoretical model attempts to fill a gap in the literature by assessing what impact an RA has on customer loyalty and the moderating effects of consumer domain expertise — product knowledge and online shopping experience.

3. The research model

Fig. 1 shows the research model of this study. As alluded earlier, many researchers argued that customer value affects customer satisfaction and in turn customer loyalty. Customer satisfaction mediates the relationship between customer value and customer loyalty. In those studies, customer value was mainly the customer perceived value of a brand product. In the marketing literature, the degree of match between product attributes and the consumer's heterogeneous taste is considered as an important dimension of product value. As related to RAs, the perceived product value is reflected by the quality of recommendation related to consumer perceived relevance of products and the degree of match.

Fig. 1. Research model.



We propose two moderator variables, product knowledge and online shopping experience, to measure individual consumer's expertise. In the collaborative-filtering RA research, similar users are identified and are used to predict scores for unrated movies. User similarity is measured by a user's past ratings on movies, which does not reflect other relevant user characteristics. In the context of RA, we identify product knowledge and online shopping experience as decision relevant user characteristics that measure consumers' expertise. We hypothesize these factors would affect customer satisfaction on the RA recommendation and the ultimate customer loyalty, respectively.

3.1. Types of RA and recommendation quality

Recommendation Quality assesses the customer's interest in and perceived value of the recommended products. Online retailers may simply promote products and special deals to their customers without using an RA. However, general product promotions without some intelligent decision making as to what product the customer may be interested in will be of limited success. Prior studies support the general notion that RA influences the perceived attractiveness of recommended products [28]. The study conducted by Diehl, Kornish, and Lynch [16] reported that the use of screening agents increases the quality of selected product. Häubl and Trifts [23] also found that RAs increased the quality of the set of products the consumers considered purchasing.

Prior studies also found the impact of RA type on recommendation effectiveness. Diehl et al. [16] reported that the type of recommendation agent affects the quality of chosen products. Further, Xiao and Benbasat [63] compared several types of RA, including content-filtering vs. collaborative-filtering, compensatory vs. non-compensatory, and feature-based vs. needs-based RA, and concluded that RA type influences users' decision effort and decision quality. Ariely et al. [4] found that collaborative filtering RAs learn more accurately about consumer preferences than individual RAs do. Both types of RAs outperform the baseline random recommendation agent. Prior research found that subjects who used the RA were more likely to select the recommended alternative than those who did not [55,61]. The findings of this prior research support the assertion that RA type affects the effectiveness of product recommendation. Moreover, collaborative filtering RA is more effective than other types of RAs. Based on this, we propose:

H1

The use of collaborative filtering RA will have a positive effect on Recommendation Quality. Specifically, a collaborative filtering RA will yield higher recommendation quality than random RA.

3.2. Recommendation quality and customer satisfaction

In measuring information systems success, a direct effect of system quality on customer satisfaction was posited in the DeLone and McLean [14] conceptual model. They proposed that an online service's system quality (e.g., ease of access to and interaction with the computer system) and information quality (e.g., timeliness, currency, convenience, and entertainment of information) are antecedents to the end-user satisfaction. In the context of recommender systems, information presented is tailored to the user's need, and the RA system provides dynamic update of information based on users' browsing patterns, thus users perceive high system quality and information quality.

From a technical point of view, recommendation quality is usually measured by accuracy of rating predictions. Error measures such as mean absolute error provide an assessment of how well the predicted ratings match actual ratings. This measure does less well at assessing whether the system can recommend valuable items previously unknown to the user. Therefore, our notion of quality moves beyond prediction accuracy but focuses on measuring user experience.

Using the movie recommender Filmtipset, which provides the underlying social network, Said et al. [53] found that "by utilizing user–user relations in a recommendation scenario one could improve the quality of recommendations." Our implementation of the RA utilizes the user–user collaborative filtering, which implicitly infers the underlying preference network for appropriate and meaningful product recommendation. To the extent that consumers find the product suggestions helpful and useful, we believe that this perception of the utility of the product suggestions will increase their level of satisfaction with the website, and consequently their shopping experience at that website. The research of both Schafer et al. [54] and Felfernig and Gula [17] supports this position. Shafer et al. [54] found that websites that make recommendations perceived as helpful and useful by customers will increase their level of satisfaction with shopping at that site. Thus we have

H2

Recommendation Quality will positively affect Consumers' Satisfaction with their online shopping experience at the merchant's website.

3.3. Recommendation quality and customer loyalty

Cumulative insights from prior studies support the general notion that customer value is an important antecedent of customer loyalty. Lam, Shankar, Erramilli and Murthy [32] argued that perceived customer value had a distinctive part to play in relation to loyalty development. Lewis and Soureli [33] reported the direct relationship between perceived value and customer loyalty. Luarn and Lin [37] also found customer value as a key determinant of loyalty. Palmatier, Scheer, and Steenkamp [44] studied not only a customer's overall loyalty to the selling firm but also the customer's loyalty vested in his or her salesperson. They found that product value perceived by the customer positively affects the loyalty to the selling firm.

In the context of RA applications, consumer perceived value results from an evaluation of the relative benefits (e.g., timely and relevant information, personalized shopping experience) and costs (e.g., time and energy consumed, stress experienced by consumers) associated with their shopping experience. Zhang et al. [64] reported that the personalized recommendation quality increases the customer loyalty by reducing product evaluation as well as search costs. Based on that we propose

H3

Recommendation Quality will positively affect Customer Loyalty.

3.4. Customer satisfaction and customer loyalty

Numerous empirical studies from the consumer goods and services literature have shown that consumer satisfaction yields consumer loyalty [7,19,60]. Walsh et al. [60] studied the relationship between consumer satisfaction and switching intentions and revealed that consumer satisfaction has a significant influence on switching intentions. The more satisfied consumers are, the more likely they are to be loyal. Oliver [43] investigated what aspect of the consumer satisfaction response has implications for loyalty and what portion of the loyalty response is due to this satisfaction. The study concludes that satisfaction is a necessary step in loyalty formation. Helgesen [25] also examined the relationship between customer satisfaction and loyalty, and found that the more satisfied a customer tends to be, the higher the loyalty of the customer. Further, Lam et al. [32] reported the significant mediating effect of customer satisfaction between customer value and customer loyalty. Cyr [13] also found the positive relationship between customer satisfaction and customer e-loyalty. Thus we propose the hypothesis

H4

Customers' Satisfaction with their online shopping experience at the merchant site will positively affect Customer Loyalty.

3.5. Product knowledge as a moderator between recommendation quality and satisfaction

In the online shopping environment, products can be generally categorized as either search products or experience products. For search products, it is relatively easy to verify and inspect product attributes before making a purchase. For experience products, it is impossible to verify or inspect the attributes without consuming the product. Movies are examples of experience goods. Aggarwal and Vaidyanathan [2] showed that collaborative-filtering RA works better than rule-based RA for experience goods. Since the assessment for experience products is more complex than that for search products, several studies observed that consumers were more likely to follow RAs' recommendations for experience products than for search products [55,63].

Xiao and Benbasat [63] further found that, the higher the product expertise of the users, the less favorable the users' evaluations of collaborative-filtering RAs. Pereira [46] investigated the interaction effects between RA type (content-filtering versus collaborative-filtering) and users' product class knowledge. The study found that users with low product class knowledge had more positive affective reactions (trust and satisfaction) to the collaborative-filtering RAs than the content-filtering RAs.

Alba and Hutchinson [3] proposed that both familiarity and the domain expertise contribute to consumer knowledge. Since expertise may affect the extent to which consumer process and analyze product related information, expert consumers are more selective in the information they acquire. Since consumer expertise directly affects consumer decision-making ability, a higher level of product related knowledge may reduce the effect of RA recommendation. Since an RA's recommendation quality has a significant effect on users' satisfaction [6], we propose the following hypothesis:

H5

The impact of recommendation quality on customer satisfaction will be negatively moderated by customers' product knowledge.

3.6. Online shopping experience as a moderator between customer satisfaction and loyalty

Satisfaction is considered a form of post-purchase attitude which is influenced by the level of consumer experience. The attitude-formation theory [47] suggests that consumer experience is a key variable that determines how attitude is formed. When the attitude is formed via the peripheral route, there is a weak connection with behavioral loyalty. When the attitude is formed via the central route, it is strongly related to behavioral loyalty. The more shopping experience a consumer has, the more likely the post-purchase attitude is formed via the central route. Thus it will positively impact customer loyalty.

Previous study has identified the moderating effect of online experience on the antecedents and consequence of online satisfaction [50]. The study found that the relationship between online satisfaction and loyalty is stronger for consumers with more online experience than for consumers with less online experience. The study also suggested that it is difficult to retain customers with less online experience, indicating the importance of online shopping experience on customer loyalty. Online shopping experience is important in our study context because nowadays many e-commerce websites use RAs. The more shopping experience a consumer has, the more likely the consumer is familiar with the interaction with RAs, and the more likely the consumer can make effective use of RAs. Based on this, we propose that consumers' experience with online purchase will strengthen the relationship between online satisfaction and loyalty.

H6

The relationship between customer satisfaction and customer loyalty is stronger for consumers with more online experience than for consumers with less online experience.

4. Research methodology

4.1. Experiment design

We conducted a lab-controlled, between-subject experiment. First, subjects were randomly assigned to either the control or treatment group. Participants filled out their pre-test questionnaire that included questions on relevant demographic data, as well as information on the subjects' level of online shopping experience and their knowledge about movies. The pre-test questionnaire also listed thirty films which were randomly selected from the 1500 most frequently rated films in the MovieLens database constructed by the GroupLens Research Group (www.movielens.org).

Second, subjects in both groups were provided with a shopping scenario and were 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.

Finally, upon completion of the online shopping simulation, subjects in both groups were asked to complete an online survey questionnaire. The final online questionnaire was used to collect data on the effectiveness of the product promotion, their satisfaction with the website and their loyalty to 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.

4.2. Measurement of study variables

4.2.1. RA type

Since prior studies have shown that CF-based RA is more effective than content-based RA in recommending experience goods, our purpose in this study is not to compare these two types of RAs. We chose CF-based RA in our implementation for two additional reasons. First, it is the most widely used RAs in industry. Notable commercial implementations of CF-based RAs include Amazon and Netflix, among numerous others. Second, because collaborative filtering RAs mimic “word-of-mouth” recommendations and use the opinions of like-minded people to generate recommendations, this type of RA is particularly relevant in social media marketing.

In our experiment, the recommendation agent manipulation was achieved by incorporating two different types of recommendation into a Web site: collaborative filtering RA vs. random recommendation. Note that the random recommendation is used to present similar interface and screen display so we can isolate these possible confounding factors that may affect users' online purchase decision. The random sampling-based recommendation algorithm has been used by other RA studies (e.g., Ariely et al. [4]).

The first step is to construct user profiles based on which we may predict user preference. To do so, we collect information on what kind of movies the participants like and dislike. As part of the pre-test questionnaire, both groups rated a set of thirty films but completed the shopping simulation using different types of RA. The control group completed the shopping simulation with a random RA which recommended five movies randomly from the 1500 films on MovieLens dataset. Each time a subject in the control group added a movie to their virtual shopping cart or viewed the product details for a movie, the Random RA randomly selected five movies to recommend.

Meanwhile, the treatment group completed the shopping task with a collaborative filtering RA. A collaborative filtering RA analyzed the film ratings of each participant in the treatment group to identify his/her unique reference user from the same MovieLens dataset. We used Pearson correlation, which measures the extent to which two variables linearly relate with each other, to calculate similarity between two users. The user-based nearest neighbor algorithm is used to select the reference users. This RA then used the current subject's reference users to select other films that the subject might also enjoy based on a prediction model that relies on weighted sum of reference users' ratings. Whenever a subject in the treatment group added a movie to their virtual shopping cart or viewed the product details for a movie, the collaborative filtering RA recommended five movies based on a collaborative filtering technique. Specifically, when the active user selected a movie, other movies that are among the highest correlations are filtered out first. For each filtered out movie, the prediction model made a prediction for the likely rating from the active user on the item. Then the top five rated items were displayed to the active user. Next time when the active user selected another movie, the same procedure was carried out and another set of five top rated movies were presented. We see that the CF-based recommendation is different from the random recommendation. For data analysis, the two types of RA are coded as 0 for random RA and 1 for collaborative filtering RA.

4.2.2. Recommendation quality

The variable "Recommendation Quality" assessed the customer's interest in and perceived value of the recommended products. The construct was measured using a scale adapted from Nysveen and Breivik [42]. The scale includes six 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 six items related to their perception of the product suggestions provided by the experimental website. The statements relate to the subject's perceived quality on the recommended movies as well as the degree to which the recommendations helped them decide what movies to buy. See Appendix A for the operationalization of the constructs.

4.2.3. Customer satisfaction

A measurement scale from the American Customer Satisfaction Index (ACSI) was adapted for measuring the dependent variable "Customer Satisfaction". The adapted scale is based on an ACSI scale for measuring users' e-commerce website satisfaction. It includes eight 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. whether they were satisfied with the products they bought and enjoyed the shopping experience). There are eight statements included in the scale with which the participants were asked to indicate their level of agreement using 7-point Likert scales.

4.2.4. Customer loyalty

Consumer loyalty has been measured in many different ways [30,57]. Kandampully and Suhartanto [29] measured customer loyalty with two items: intention to recommend and intention to repurchase. For this study consumer loyalty was measured by three items adapted from the University of Michigan ACSI website.

4.2.5. Product knowledge

Consumer expertise is defined as the consumer's ability to perform product related tasks successfully [3]. Product knowledge is highly relevant to consumer domain expertise. Product knowledge was measured using two 7-item scales in the study conducted by Swaminathan [59]. Zhang et al. [64] measured participants' product knowledge using a single item — the total number of items they had watched out of 134 items included in their experiment. In this study, participants answered three questions related to their prior product knowledge. Answers were also captured on a 7-point Likert scale and asked the participant to rate their level of agreement with three items related to their familiarity with movies and movie purchase.

4.2.6. Online shopping experience

As mentioned, a consumer's online shopping experience is deemed relevant to measure the consumer's familiarity with and ability to effectively use RAs, as many e-commerce websites have implemented RAs. Novak et al. [41] measured consumers' online experience by considering their skills of using the web as a tool to search information. Rodgers et al. [50] measured consumers' online experience by assessing the amount and frequency of web-based support system use. In this study, online shopping experience was measured by three items. The scale relates a subject's experience in using the Internet as a channel to make purchase and to search for information. The scale used 7-point Likert scales and asked the participant to rate their level of agreement with three items related to their experience in online shopping.

5. 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 active consumers of such products. The results from this study are clearly generalizable to the population at large engaged in this area of commerce. The ages of the participants ranged from seventeen to fifty-seven. 62% of the subjects were male (156) and 38% were female (95). Table 1 below provides a summary of the study population.

Table 1. Study population 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
Study population	251	156	95	22.52	6.6

Two-tailed independent sample *t*-test was performed to test for differences between the control group and the treatment group for all thirty-two pretest questionnaire survey items. The pretest results showed that homogeneity of variance between the treatment and control groups held for all items. There were no significant differences between the two groups regarding their experience with personal computers, knowledge of Internet and online shopping on the Internet at the 0.05 significance level.

The descriptive statistics of the five main study variables are shown in Table 2. The different number of observations for the various groups is due to missing data. Further note that the three main variables studied here (RA, CS, CL) have mean values higher for the treatment group than for the controlled group. This is an initial indication of support for this study's results. The moderator variables (PK, OS) are comparable across the control and treatment groups. We will formally test the hypotheses in later sections.

Table 2. Descriptive statistics of study variables.

Variables	N	Mean	STD	Control group			treatment group		
				N	Mean	STD	N	Mean	STD
Recommendation Quality (RA)	244	3.89	1.49	114	3.10	1.40	130	4.48	1.20
Customer Satisfaction with website (CS)	244	4.23	1.40	114	3.93	1.49	130	4.49	1.27
Customer Loyalty (CL)	244	3.72	1.67	114	3.35	1.69	130	4.04	1.59
Product Knowledge (PK)	220	5.34	1.29	101	5.15	1.37	119	5.49	1.19
Online Shopping Experience (OS)	250	3.34	1.98	116	3.22	1.89	134	3.42	1.98

5.1. Measurement model

The research model is multistage, indicating the need for structural equation modeling techniques that simultaneously test multiple relationships. Statistical tools used to analyze the data included SPSS, AMOS [10], and SmartPLS [49]. A basic analysis of the collected data, including a test for item normality, means, STD and outliers, was performed using SPSS. Similar to LISREL, AMOS is based on covariance and provides various overall goodness- of-fit indices; thus, it is recognized more confirmatory in nature [10].

The overall measurement model provided an acceptable fit with Chi-square/degrees of freedom ratio of 2.28, which is within the recommended range between 1 and 3. The measurement model produced a comparative fit index (CFI) value of 0.944, which is larger than 0.9 for a well-fitting model. The Normed Fit Index (NFI) is 0.906. The Non-Normed Fit Index (NNFI) is 0.929, which is larger than the acceptable level of 0.9. The value of RMSEA was 0.072, which is less than 0.08 suggested for good model fit [8]. 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. We thus proceed to analyze convergent and discriminant validity with Confirmatory Factor Analysis (CFA) using AMOS.

Convergent validity was tested using three criteria suggested by Fornell and Larcker [18]; 1) all scale items should have loading that is higher than 0.6 on their respective scale; 2) the average variance extracted (AVE) for each construct should be larger than 0.5; and 3) composite reliability of each construct should exceed 0.8. Table 3 provides the factor loadings of all items considered in this study. All items have factor loadings that are significant and larger than the recommended cutoff of 0.6. Table 4 shows Cronbach's alpha, composite reliability, the average variance extracted (AVE), and the correlations between constructs. Cronbach's alpha and composite reliability are measures of internal consistency. Unlike Cronbach's alpha, the composite reliability takes into account the actual loadings used to construct factor scores. The Cronbach's alpha values of all constructs are larger than the acceptable level of 0.7, and the lowest composite reliability of all constructs is 0.82, indicating good internal consistency. The lowest AVE among all constructs is 0.60, which is higher than the acceptable threshold of 0.5. Therefore, all of the constructs in the measurement model exceed the threshold judged to be acceptable for convergent validity.

Table 3. Confirmatory factor analysis results.

Model path	**Factor loading**	**Critical ratio**
RQ1 ← Recommendation Quality	0.82	Fixed
RQ2 ← Recommendation Quality	0.83	15.82
RQ3 ← Recommendation Quality	0.81	14.89
RQ4 ← Recommendation Quality	0.92	18.08
RQ5 ← Recommendation Quality	0.91	17.79
RQ6 ← Recommendation Quality	0.77	13.92

Model path	Factor loading	Critical ratio
CS1 ← Customer Satisfaction with website	0.75	Fixed
CS2 ← Customer Satisfaction with website	0.74	11.93
CS3 ← Customer Satisfaction with website	0.78	12.77
CS4 ← Customer Satisfaction with website	0.86	14.22
CS5 ← Customer Satisfaction with website	0.90	14.82
CS6 ← Customer Satisfaction with website	0.89	14.59
CS7 ← Customer Satisfaction with website	0.76	12.32
CS8 ← Customer Satisfaction with website	0.89	14.59
CL1 ← Customer Loyalty	0.95	Fixed
CL2 ← Customer Loyalty	0.94	30.26
Cl3 ← Customer Loyalty	0.94	30.63
PK1 ← Product Knowledge	0.71	Fixed
PK2 ← Product Knowledge	0.83	10.04
PK3 ← Product Knowledge	0.78	9.95
OS1 ← Online Shopping Experience	0.84	Fixed
OS2 ← Online Shopping Experience	0.85	9.95

Table 4. Reliability, construct correlations and discriminant validity.

	Cronbach's α	Composite reliability	AVE	RQ	CS	CL	PK	OS
RQ	0.94	0.94	0.71	0**.84**				
CS	0.94	0.92	0.68	0.58	0**.82**			
CL	0.94	0.96	0.89	0.63	0.81	0**.94**		
PK	0.82	0.82	0.60	0.28	0.17	0.29	0**.78**	
OS	0.83	0.83	0.72	0.08	0.07	0.13	0.78	0**.85**

RQ: Recommendation Quality; CS: Customer Satisfaction; CL: Customer Loyalty; PK: Product Knowledge; OS: Online Shopping Experience.

For discriminant validity, all construct AVE estimates should be larger than the corresponding squared interconstruct correlation estimates. The off-diagonal elements represent square root of AVE value for the corresponding construct.

To assess discriminant validity, the AVE of the latent constructs should be larger than the corresponding squared inter-construct correlation estimates. This indicates the measured variables have more in common with the construct they are associated with than they do with the other constructs. The square root of AVE value for the corresponding construct, the diagonal elements in Table 4, is larger than the corresponding inter-construct correlation estimates, showing good evidence of discriminant validity.

5.2. Results from hypothesis testing and the structural model

Chin et al. [11] suggested that, in formulating and testing for interaction effects using PLS, we follow a hierarchical process similar to that used in multiple regression in which one compares the results of two models: with and without the interaction construct. Following this suggestion, we test the hypothesized relationships among the constructs and the moderating effect of online shopping experience on the research model using Partial Least Squares with the software program SmartPls [49]. The path coefficients of research models are shown in Table 5. Model 1 represents the reduced research model without the moderating variable of product knowledge and online shopping experience. Model 2 represents the research model with all study variables, including the two moderating variables. Model 3 is the full model that includes the interaction effect of Recommendation Quality and Product Knowledge on Customer Satisfaction, as well as the interaction effect of Customer Satisfaction and Online Shopping experience on Customer Loyalty. We employed a bootstrapping method (500 times) that used randomly selected subsamples to test the PLS model.

Table 5. Results for the structural model.

Construct	Model 1	Model 2	Model 3
Direct effect			
RA Type → RQ	0.42***	0.42***	0.42***
RQ → CS	0.67***	0.66***	0.65***
CS → CL	0.63***	0.63***	0.62***
RQ → CL	0.27***	0.26***	0.26***
PK → CS		0.03	0.001
OS → CL		0.05	0.05
Interaction effect			
PK ∗ RQ → CS			− 0.10*

Construct	Model 1	Model 2	Model 3
CS ∗ OS → CL			− 0.03
R^2			
RQ	0.18	0.18	0.18
CS	0.45	0.45	0.46
CL	0.69	0.70	0.70

∗∗∗ $p < 0.001$.

∗ $p < 0.05$.

H1 proposed that a Collaborative Filtering RA would yield higher Recommendation Quality than a Random RA. Our study result supports this assertion; the path coefficient on Model 1 is 0.42 and $p < 0.001$. H2 states that Recommendation Quality will positively affect Customer Satisfaction. The path coefficient on Model 1 is 0.67 and $p < 0.001$, supporting hypothesis 2. In H3, we proposed a relationship between Recommendation Quality and Customer Loyalty. The path coefficient on Model 1 is 0.27 and significant at $p < 0.001$, suggesting that recommendation quality yields higher customer loyalty, confirming hypothesis 3. H4 states that Customer Satisfaction is positively related to Customer Loyalty. The result shows the path coefficient of 0.63, supporting hypothesis 4. In H5, we proposed that the impact of recommendation quality on customer satisfaction will be negatively moderated by customers' product knowledge. The study results support this assertion; the path coefficient of the interaction term in Model 3 is − 0.10 and $p < 0.05$. Finally, H6 states the relationship between customer satisfaction and customer loyalty will be positively moderated by consumers' online shopping experience. However, our result does not support this hypothesis. The path coefficient of the interaction term in Model 3 is − 0.03, but the test effect is not statistically significant at the 0.05 level.

The explanatory power of a structural model can be evaluated by the squared multiple correlation (R^2) value of the final dependent construct. It is also instructive to examine the R^2 values for the intermediate variables in the structural model. The final dependent construct in this study, Customer Loyalty, has the R^2 value of 0.70 for the full model, indicating that the model accounts for 70% of the variance in the dependent variable. The R^2 value of Customer Satisfaction's variance is 0.45 in Model 1. 45% of customer satisfaction's total variance is explained by RA Type and Recommendation Quality. The inclusion of the interaction terms between Recommendation Quality and Product Knowledge raises the R^2 value of Customer Satisfaction's variance to 0.46 in Model 3. Further, the R^2 value of Recommendation Quality is 0.18 for all models. These R^2 values for the path coefficients are all significant at the 0.05 level or below.

A moderator is a variable that affects the strength or direction of a relationship between an independent variable and a dependent variable [5]. First, the impact of PK on the strength of the relationship between RQ and CS can be seen by examining the explained variance. The slight increase of R-square from 0.45 to 0.46 does not show strong influence of the moderator on the strength of the relationship. Second, moderation of the direction of the relationship is detected by looking at the interaction effects. The significant regression coefficient for the interaction terms (with path coefficient − 0.1 and is significant at 0.05 level) indicates PK negatively impact the relationship between RQ and CS.

Similarly, the slight increase of R-square from 0.69 to 0.70 for the Customer Loyalty does not show strong influence of the online shopping experience on the strength of the relationship between customer satisfaction and loyalty. The insignificant regression coefficient for the interaction terms (− 0.03) does not support the positive direction of the relationship by the moderator. Different from the customer loyalty literature that consumers' online experience directly affects customer loyalty, we find the use of RA can mitigate the effect of consumers' lack of experience and therefore customer loyalty is not undermined with inexperienced consumers.

5.3. Summary results from testing the path analytic model

There are two types of relationships between variables in our structured model: direct effect and indirect effect. The direct effect exists if two variables are directly connected with a path link indicating a causal relationship: e.g., RA Type → Recommendation Quality. The indirect effect exists if there is more than one path between the two variables; i.e., the two variables affect each other through other variables (e.g., RA Type → Recommendation Quality → Customer Loyalty). The direct–indirect–total effects among variables are presented in Table 6.

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

Relationships between constructs	Direct effect	Indirect effect	Total effect
RA Type → Recommendation Quality	0.42		0.42
RA Type → Customer Satisfaction		0.28	0.28
RA Type → Customer Loyalty		0.28	0.28
Recommendation Quality → Customer Satisfaction	0.66		0.66
Recommendation Quality → Customer Loyalty	0.26	0.42	0.68
Customer Satisfaction → Customer Loyalty	0.63		0.63
Product Knowledge → Customer Satisfaction	0.03		0.03
Product Knowledge → Customer Loyalty		0.02	0.02
Online Shopping Experience → Customer Loyalty	0.05		0.05

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 RA Use on Customer Satisfaction is 0.42 × 0.66 = 0.28. The total effects equal the sum of the direct and indirect effects. As seen in Table 5, the direct effect of Recommendation Quality on Customer Loyalty is 0.26, and the indirect effect is 0.66 × 0.63 = 0.42; thus, the total effect of Recommendation Quality on Customer Loyalty is 0.26 + 0.42 = 0.68. The analysis of the total effects reveals that Customer Satisfaction on Customer Loyalty is among the highest (0.63), which is consistent with the literature in the context of RA. In addition, the impacts of Recommendation Quality on Customer Satisfaction and Customer Loyalty are highest (0.66 and 0.68 respectively), implying the importance of quality recommendation on these outcome variables. The impact of RA type on Recommendation Quality is also relatively high (0.42).

The direct effect of Product Knowledge on Customer Satisfaction is very small (0.03). However, compared with Table 5 we see the interaction between Product Knowledge and Recommendation Quality has a negative effect on Customer Satisfaction. The negative moderating effect of product knowledge on customer satisfaction shows that more effective RAs should provide novel recommendations. Finally, the direct effect of consumers' online shopping experience on customer loyalty is very small (0.05). In contrast with Product Knowledge, the Online Shopping experience does not have a strong interactive effect on customer loyalty.

6. Summary, conclusions, and implications

The primary study objectives were from a social media marketing perspective, to experimentally assess the moderating effect of consumer product knowledge and online shopping experience on the relationship between RA use and customer loyalty. As expected, the results clearly confirmed the relationship between customer loyalty and satisfaction with the website, both critical variables for success in B2C e-commerce. Close to 70% of the variance in customer loyalty can be explained by customer satisfaction with the website as measured here and RA recommendation quality combined. The results show that effective RA use has a significant impact enhancing recommendation quality, which in turn directly affects customer satisfaction with the website. Further, product knowledge is shown to negatively moderate the relationship between RA recommendation quality and customer satisfaction with the website. Thus, with the increasing level of customer product knowledge, it becomes less influential RA recommendation quality towards generating satisfaction with the website. Last, consumers' online shopping experience has shown no significant effect on the relationship between customer satisfaction and customer loyalty. Overall, the results confirm significant business value from RA use for B2C e-commerce.

6.1. Implications for theory

This study makes two important contributions to the research literature. First, previous studies have not experimentally tested the impact of RAs on customer loyalty. Drawing on the well-tested model of customer loyalty, we provide a theoretical justification for this impact by regarding recommendation quality as cognition, customer satisfaction as affect, and customer loyalty as behavior. This study bridges the gap between customer loyalty and recommendation agent research studies by theoretically and empirically exploring the effect of RA use on customer loyalty through customer satisfaction and recommendation quality. The framework developed in this study offers a fresh perspective on the effective use of RAs on customer loyalty and can serve as the foundation for future research.

Second, drawing on the theory of customer loyalty, human information processing theory, and interpersonal similarity, this study integrates RAs and consumers' domain expertise (product knowledge and online shopping experience) with the customer loyalty theoretical framework and examines their combined impact on loyalty. We provided a theoretical explanation for how the use of an RA and product knowledge affect customer satisfaction and provide evidence that the consumers' online shopping experience does not significantly impact customer loyalty with the use of an RA. The empirical results provide insights into the complex interrelationships between the use of RAs, product knowledge, online shopping experience, recommendation quality, customer satisfaction, and customer loyalty constructs; all important theoretical constructs for the foreseeable future. Thus we have extended prior research by providing insights into their interrelationships.

6.2. Implications for practice

The results from this study provide practitioners with more information on which to base their decisions for RA design and implementations in their e-commerce websites, providing some insights to aid online businesses in determining the most effective strategies for reaching and serving their customer base. In today's information overloaded Internet/WWW environment with increasingly knowledgeable and experienced consumers, effectively using RAs to support consumers accessing e-commerce websites means these systems must be designed with a greater understanding of the needs and interests of individual users or user groups, and user shopping experience and interests. It also means providing product information ranging from general to quite specific, in order to serve individual customers appropriately. For example, users with sufficient product knowledge will be likely interested in recommendations for items he/she has already consumed so that he/she can evaluate the recommendation quality, while at the same time recommendations for novel items will be more valuable to these users. Thus, the knowledge delivery system must be very flexible, allowing customers to choose the level of detail, as well as answer customer questions about specific products or product groups from different perspectives relevant to the customer. Last, managers should continuously, or at least periodically, conduct customer opinion surveys searching for ways to recommend new, novel products and increase user satisfaction with the websites. We recommend that in the design and implementation of future RAs, developers recognize the need for different approaches to customer shopping decision support, based on specific user characteristics such as their specific product knowledge and past online shopping experience.

The insights gained in this study provide a basis for projecting the potential benefits of deploying RAs to a much broader business arena. The use of RAs can be useful for individual shoppers at home or at work for saving time and improving shopping decision quality. As Internet shopping proliferates, the use of decision aids such as RAs becomes increasingly necessary. It is important for business marketers considering an e-commerce sales strategy to understand the potential positive and negative implications RAs have in the online shopping space. Those organizations that understand the importance of this new technology and its business impact will be better positioned to compete in the networked markets. In the immediate future it may not be enough just to provide consumers with a large selection of products to browse. Websites implementing effective technology to assist consumers through the online shopping experience are likely to gain a distinctive advantage. Shopbots and other forms of RAs are likely to play an integral role in the design of new marketing strategies. This is an evolutionary process in which both business marketers and consumers learn about the potential benefits and limitations of RAs as decision support tools. Obviously, the characteristics of specific RAs 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 study but provides a strong invitation for practitioners and researchers to work together toward this important goal. The following section explores some possibilities.

6.3. Study limitations and opportunities

Classic collaborative filtering techniques match users with their nearest neighbors inferred by their past item ratings. Prior research shows that in taste domain, people prefer recommendations from people they know. For example, Said et al. [53] showed that user similarity in movie taste correlates to the social relations between users. By focusing on not only the items, but also the interests, hobbies, and keywords the users have in common, the task of finding like-minded users can be made significantly easier. Social recommender systems would make use of users' social profile data (common interest, hobbies, etc.) as additional basis to increase recommendation trustworthiness. Future research should examine how information created and exchanged through social media can be integrated into the recommender systems to deliver better user experience.

Future research studies also could compare the impact of different types of RAs on the buying process to see which type of RAs seems to be the most effective. In addition, further research with the theoretical model developed for this study might also examine how changes in product characteristics such as price categories, frequency of use, etc. may affect the impact RAs have on customer decision support, satisfaction with the website, and customer loyalty.

While this study provided useful insights into the use of RAs 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 RAs. 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 RAs has great potential as a business tool. Perhaps by answering some of the questions presented here, we can continue to identify new opportunities to use increasingly more effective and sophisticated RAs to improve the way in which consumers use online shopping to enhance their lives and fulfill their needs.

APPENDIX A

Measurement scale used for Recommendation Quality - adapted from Nysveen and Breivik [42]

1. [PA1] The movie suggestions were helpful.
2. [PA2] The movie suggestions were relevant.
3. [PA3] I became interested in a movie after it was suggested by the website.
4. [PA4] I liked the movies suggested by the website.
5. [PA5] The website suggested the kinds of movies I like.

Measurement scale used for Customer Satisfaction - adapted from ACSI website survey

1. [CS1] I was able to accomplish what I wanted to on this website.
2. [CS2] This website was well organized.
3. [CS3] I was able to find the information I wanted on this website.
4. [CS4] This website met my expectations.
5. [CS5] This website compares favorably to my idea of an ideal website.
6. [CS6] I enjoyed shopping on this website.
7. [CS7] This website had a good selection of products to choose from.
8. [CS8] I feel this website provides a good shopping experience.

Measurement scale used for Product Knowledge

1. [KN1] I frequently watch movies at home.
2. [KN2] I have seen a wide variety of movies.
3. [KN3] I know many details about the movies I have seen.

Measurement scale used for Loyalty – adapted from ACSI website survey

1. [LO1] It is likely that I will return to this website.
2. [LO2] I am likely to recommend this website to someone else.
3. [LO3] I am likely to continue to use this website to buy movies.

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