Winter 12-6-2018

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Zhao, X.P., Gu, T.L., Liu, J. & Tian, B.B. (2018). The marketing effects of recommender systems in a B2C e-commerce context: A review and future directions. In *Proceedings of The 18th International Conference on E lectronic Business* (pp. 665-672). ICEB, Guilin, China, December 2-6.

The Marketing Effects of Recommender Systems in a B2C E-commerce Context: A Review and Future Directions

(Full Paper)

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ABSTRACT

As a kind of digital marketing technology, recommender systems (RSs) have already been widely applied for online retailers. Empirical studies have proved that RSs can increase the number of items sold, sell more diverse items, increase the user satisfaction and user fidelity and so on. However, our understanding of the marketing effects of RSs is still fragmented. Few comprehensive literature reviews has been published. This paper mainly reviews and synthesizes extant related literature in the last five years on the marketing effects of RSs, specifically focuses on how RSs influence consumers' decision quality ,product demand and retailer profits in e-commerce market and e-commerce companies. From the angles of consumer behavior and marketing strategies, this study aims to discuss the positive and negative impacts which RSs bring to consumer and its providers, and presents some suggestions and potential directions for future research on RSs.

Keywords: Recommender systems, marketing effects, consumer decision-making, e-commerce market, online retailers.

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INTRODUCTION

With the rapid development of Internet and e-commerce technology, online shopping has become an important part of people's daily life. According to data released by CIECC, the global online retail transaction volume reached $2.304 trillion in 2017, an increase of 24.8% compared with 2016. And the proportion of online retail transaction volume to global retail sales increased from 8.6% in 2016 to 10.2%. In China, e-commerce has already occupied more than 60% of the network economy. Recommender systems are software tools and techniques which have proven to be a valuable means of coping with the information overload problems in the e-commerce websites. As users found it difficult to arrive at the most appropriate choices from the immense variety of items (products and services) that these websites offered. Amazon claimed that 35% of its sales are attributed to the recommendation systems. Dangdang's senior development director Fu Qiang gave a set of data: only need a technical team of dozens of people, the average daily contribution of recommended products can be worth 50% of the sales contribution of some business units. Recommender technology has become an important marketing tool for B2C e-commerce websites.

From the business perspective, RS provides new opportunities and means to implement known effective marketing strategies, such as personal targeting or dynamic pricing, incorporating various price and profit-related information into recommendation process, and at the same time achieving the proper balance between consumer's needs and suppliers' purposes. However, there has been relatively less studies on RSs in the business-oriented areas such as management science, consumer behavior and marketing than studies in technology-oriented areas such as computer science and information systems (Michalis & Michael, 2013). In recent years, many domestic and foreign scholars have summarized the research progress of e-commerce RSs. But those study reviews mainly focus on the recommendation algorithms and models, RSs evaluation and RSs' impact on consumer online shopping behavior and so on (Sun et al., 2017; Sun, Zhang, &Wang, 2016; Xiao & Benbasat, 2014), less on the economic effectiveness of recommendations. A study by Yang, Wang, and Sun (2016) explored the marketing effects of the RS on consumers and its influencing factors based on the consumer perspective. They presented that the characteristics of the shopping website, RS and recommendation information influence the marketing effect of the RS on consumers, but did not involve the actual interests of e-commerce vendors. Li and Karahanna (2015) proposed that more attention should be paid to the actual impact of recommendation systems on e-commerce markets and e-commerce companies. Therefore, the main objective of the current paper is to review empirical studies on e-commerce product recommendation systems published in the last five years, particularly focuses on the impact of RS on consumers' decision quality and its economic effectiveness such as increase in product demand and retailers' profits in e-commerce market and e-commerce companies. This study synthesizes empirical findings in each area to show the extant state of understanding on the impact of RS, and presents some suggestions and potential directions for future research on B2C e-commerce product recommender systems.

IMPCTS ON CONSUMER DECISION-MAKING

Consumer Intention to Adopt RS

RS in the e-commerce context refers to a web-based technology that explicitly or implicitly collects a consumer's preferences and recommend tailored e-vendors' products or services accordingly. As a type of interactive decision aid tool, if consumers believe that the RS has no value or is unwilling to adopt the recommended products, there will be no impact on consumer decision-making at all (Li & Karahanna, 2015). In other words, consumer's adoption of RS is a prerequisite for consumer decision-making and a prerequisite for economic effectiveness in market and companies.

In order to study whether users accept and adopt RS, scholars based on theoretical models such as technology acceptance model (TAM) and the theory of reasoned action (TRA), combined with consumer factors and system factors to study the consumer's willingness to use RS. Table 1 summarizes existing studies in this area.

In terms of consumer factors, scholars mainly study the subjective feelings of consumers on RSs and the characteristics of consumers themselves, including subjective norm, satisfaction, trust, perceived care, perceived pleasure, perceived usefulness and perceived ease of use.

For system factors, Ku, Peng, and Yang (2014) and Ozok, Fan, and Norcio (2010) pointed out that the price, image and name of products in the personalized recommendation interface are regarded as important information. Product promotions, user ratings, and feedback are identified as secondary information types. And they suggested recommending up to three recommendations on a single page. Lately, some scholars have analyzed the influence of the relationship between the social existence characteristics of the RS interface and trust on the adoption of RS by consumers. This social existence refers to the anthropomorphic characteristics of the RS, such as humanoid avatars and human voices, is positively affecting consumers' willingness to adopt the RS (Etemad-Sajadi, 2016; Wang et al., 2016).

Impacts on Consumer Decision-Making

A complete decision includes both the decision process and the decision outcome. Personalized recommendation not only affects product evaluation, product preferences, decision effort in the decision-making process of consumers, but also influences the decision quality, decision confidence and final purchase choices of decision-making results (Xiao & Benbasat, 2014). For example, F. Huseynov, S.Y. Huseynov, and Özkan (2016) assessed the impact of knowledge-based recommender agents on the online-consumer decision-making processes through objective measures and found that they improve consumer decision-making process by reducing the shopping duration and effort spent in searching for suitable products. Xu, Benbasat, and Cenfetelli (2017) proposed and empirically evaluated a two-stage model of generating product advice using recommendations in the first stage and RI functionality in the second stage. Results show that the complementary synergies between the two stages result in higher perceived decision quality, but at the expense of higher perceived decision effort.

Since the overall purpose of personalized recommendations is to influence the consumer's final purchase choice throughout the consumer's overall purchase decision. According to the two-stage theory of consumer purchase decision, in the selection stage, consumers will carefully evaluate and compare the products in the selected set, and finally make a purchase decision. At this stage, consumers will have a certain degree of desire for a certain product. The higher the degree of craving, the stronger the willingness to purchase, and the greater the possibility of final purchase. Therefore, many researchers have studied the impacts of personalized recommendations on consumers' willingness to purchase, and mainly focused on online consumer reviews of recommended products.

Product reviews are an increasingly important type of user-generated content as they offer a valuable source of information. Product manufacturers and designers, e-commerce websites, and potential consumers can all potentially benefit from the posted data. Baum and Spann (2014) analyzed the interplay between online consumer reviews and recommender systems and its effects on consumers' decision making. The main results are that providing online consumer reviews does not necessarily have to be beneficial for an online retailer, as inconsistent recommendations do negatively influence consumers' purchase decisions. In addition, by providing positive opinions of previous customers to a recommender system's recommendation, online retailers may increase the effectiveness of their recommender system. However, if a previous customer's recommendation contradicts that of a recommender system, positive consumer reviews may even have negative consequences for online retailers. Yao and Cui (2017) pointed out that the location on web page and WOM direction of recommended commodities have significantly positive influence on consumers' purchase intention, but the number of online WOM of recommendations has weak influence on consumers' purchase intention. Benlian, Titah, and Hess (2012) tested a conceptual model linking provider recommendations(PR) and consumer reviews (CR) to four consumer beliefs (perceived usefulness, perceived ease of use, perceived affective quality, and trust) in two different product settings (search products vs. experience products). Users of PR express significantly higher perceived usefulness and perceived ease of use than users of CR, while users of CR express higher trusting beliefs and perceived affective quality than users of PR, resulting in different effect mechanisms towards OPR reuse and purchase intentions in e-Commerce transactions. Further, CR were found to elicit higher perceived usefulness, trusting beliefs and perceived affective quality for experience goods, while PR were found to unfold higher effects on all of these variables for search goods.

Table 1: Empirical Studies on Consumer Intention to Adopt RS

Paper	Conceptual foundation	Variables	Major findings
Martínez-López *et al.* （2015）	Theory of reasoned action; Technology acceptance model; Trust-TAM; Theory of planned behavior	Perceived ease of use, perceived usefulness, trust，familiarity，perceived risk, perceived behavior control, subjective norms	Trust and perceived usefulness of the recommender stand out as the determining factors of its use, though the consumer's attitude toward the recommender and others' opinion of its use also have significant influence too.
Dai *et al.* （2015）	Consumer behavior theory; Consumer value theory	Functional value, social value, emotional value, epistemic value, conditional value	Functional value, social value and emotional value factors are the key factors that mainly affect users' adoption of personalized recommendations, while cognitive value and conditional value factors have relatively low impact.
Wang *et al.* （2017）	The modification of technology acceptance model(TAM2)	Subjective norm, perceived personalization, quality of recommendation, perceived ease of use, perceived usefulness, perceived mobility, privacy concerns, users' innovativeness	Users' innovativeness and perceived usefulness have significant positive effects on users' adoption on personalized recommendation, while the privacy concerns have negative impacts on users' adoption.
Wang & Benbasat （2016）	Trust-TAM; Attribution theory; The effort-accuracy-restrictiveness (ERA)	Trust, advice quality, perceived cognitive effort, perceived strategy restrictiveness, transparency	Three performance factors affect only the competence belief, whereas perceived RA transparency influences all three trusting beliefs. The effects of perceived transparency on competence are partially mediated by perceived cognitive effort and advice quality
Yang *et al.* （2016）	The information systems success model ; Technology acceptance model	Website service quality, quality, recommender system quality, recommendation information quality, perceived usefulness，perceived ease of use	Recommendation information quality has the strongest total effect on adoption intention of recommendations，followed by website service quality and recommender system quality，respectively.
Chen & Pu （2014）	Multi-attribution utility theory; Theory of reasoned action; Technology acceptance model; The theory of planned behavior	Competence constructs, trustworthiness, decision quality, behavioral intentions	The ORG performed significantly better in terms of enhancing users' perceived recommendation quality, perceived ease of use and perceived usefulness of the system.
Zhang & Curley （2018）	Advice taking theory; Trust theory	Explanation availability, explanation mode, perceived personalization, trust	Effects of both the availability and mode of explanations on consumers' trust beliefs are found to be mediated by consumer's perceived personalization of the RA that, in turn, mediate the effects on intention to use.
Choi et *al.* （2014）	Theory of reasoned action; Innovation diffusion theory	Perceived ease of use, perceived recommendation quality, perceived enjoyment, social influence, Mobility, collectivism, uncertainty avoidance	Functional and social factors have significant impacts on user attitudes towards mobile recommender systems. The relationships between belief factors and attitudes are moderated by two cultural values: collectivism and uncertainty avoidance.

Source: This study.

In response to the importance of consumer reviews, studies have proposed to improve the quality of the top reviews shown to a user when he/she is investigating some product. Yu et al., (2013) took the coverage of product aspects into consideration as well as the overall quality of the top reviews set. Tu, Cheung, and Mamoulis (2017) considered the personal preferences of users in review recommendation, by selecting a personalized top reviews set (PTRS), which includes reviews of which the content is related to the aspects important to the user. Experiments showed that their methodology selects reviews that focus more on the product aspects that are important to the user, without sacrificing coverage and high degree of quality.

IMPACTS ON MARKET AND ONLINE RETAILERS

Most of the studies on the impact of RSs on consumer decision-making are based on the self-reported behavior intention of the participants and the "return willingness" or "purchase intention" of asking them, for example, self-report after using the recommendation system. However, in many cases, these user studies do not involve any actual purchasing decisions. So analyzing the actual data of e-commerce platform trading activities, including sales data or consumer behavior data, has become the direction of researchers to further study the impacts of RSs on market and online retailers.

Impacts on Product Demand and Product Sales

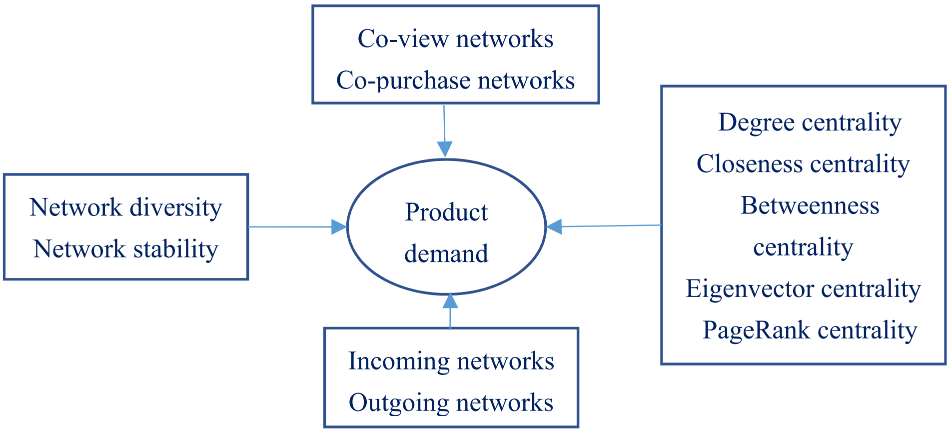
In e-commerce contexts, a recommender can encourage a consumer to buy, orient their decisions towards specific directions (e.g., by fostering or avoiding the purchase of specific items), and ultimately, increase sales. Cremonesi, Garzotto, and Turrin (2012) explored the persuasiveness of RSs in the context of large interactive TV services. Research results show that RSs can affect the lift factor and conversion rate, which is a clear increase in sales and affects the user's actual purchase decision for the recommended product, while the introduction of an RS tends to diversify the purchase and orient users towards less obvious choices (the long tail). The findings of Panniello, Gorgoglione, and Tuzhilin (2016) indicate that by transitivity, using contextual information in RSs can improve accuracy and diversification, which in turn affects trust, which, finally, affects purchases (measured by quantity of items purchased and by the customers' expenditure). Using data on the digital camera category from the largest business-to-consumer platform in china, Tmall.com, Lin (2014) assessed the relative impact of user recommendations and system recommendations on the sales of products in e-commerce, and further explored the interaction effects between these two recommendations. The main results are that a 1% increase in the volume (valence) of user recommendations on a product increases the product's sales quantity by 0.013% (0.022%), whereas a 1% increase in the strength of system recommendations on a product increases the product's sales quantity by 0.006%. They also highlighted that user recommendations are more effective than system recommendations in driving product sales.

As recommenders provided visible connections to recommended products, RSs can eventually form a visible directed product recommendation network where products (i.e., network nodes) are explicitly connected by hyperlinks (i.e., network ties). Thus, some researchers were particularly interested in the impact of RS on product demand from the recommendation network's perspective. Lin, Goh, and Heng (2017) investigated the effects of network diversity and network stability on product demand in an e-commerce setting. Controlling for relevant factors at the individual product, pricing, product network, product category, and time unit levels, they found that a 1% increase in the category diversity of the incoming (outgoing) co-purchase network of a product is associated with a 0.011% (0.012%) increase (decrease) in the product's demand, while a 1% increase in the stability of the outgoing co-purchase network is associated with a 0.012% decrease in demand. And the co-purchase recommendation network has a stronger association with product demand than the co-view recommendation network for both network diversity and stability. According to Jabr and Zheng (2014), once products are hyperlinked through recommendations, those with higher centrality within the resulting network of referrals are associated with higher sales. However, the central position of competitive products plays an opposite role in the sales of focal products. The higher level of centrality of competitive products enhances its appeal, but weakens the centrality of the focal products.

Some research work specifically investigated the demand effects of co-purchase recommendation networks using data collected from the product network of books on Amazon.com (Oestreicher-Singer & Sundararajan, 2012; Oestreicher-Singer et al., 2013). The main empirical findings suggest that the visibility of the product network can result in up to a threefold average increase in the influence that complementary products have on one another's demand. Moreover, if the product is evaluated solely on direct revenue, regardless of its network value, then the value of low sellers may be underestimated, whereas the value of best sellers may be overestimated. In addition, Leem and Chun (2014) provided a new perspective on how Social Network Analysis (SNA) can be used to study the influence on product demand by the recommendation network. The result of regression analysis demonstrates that five of six SNA measures in the recommendation network have a significant effect towards demand, and then the largest effect towards a book's demand is associated with degree centrality.

Impacts on Market Prices and Advertising Strategies

A recommender system deployed by an electronic marketplace functions as a medium for targeted advertising for sellers, analogous to traditional advertising media such as TV, newspaper, and, recently, the Internet. When the purpose of recommendations as well as seller advertising is creating consumer awareness about products, the presence of the recommender system poses new challenges to sellers in electronic marketplaces regarding their advertising and pricing decisions. Li, Chen, and Raghunathan (2016) examined the intricate interaction between competing sellers' advertising and pricing strategies in the presence of a recommender system in an electronic marketplace. Research results show that the impacts of the RS are the result of a subtle interaction between advertising effect and competition effect. The advertising effect causes sellers to advertise less on their own and the competition effect causes them to decrease prices in the presence of RS. Since RS has become ubiquitous in electronic marketplaces and precisions of these systems have been continuously improving, a pertinent question relates to how RS precision affects the sellers and consumers in marketplaces with the RSs. This research found that an increase in the RS precision softens the price competition. On the other hand, increased RS precision implies that consumers are more likely to buy the product suggested by the RS, thus reducing the marginal benefit from sellers' advertising and limiting their incentives to advertise. Consequently, "sellers' advertising level follows an inverse U-shape with recommender system precision" (p. 6).



Source: This study.

Figure 1: Recommendation Networks and Product Demand.

Increasing Retailers Profits

Maximizing profits by estimating consumers' willingness to pay for recommended products

Consumers' willingness to pay (WTP) and their utilities for different products are indispensable inputs for many prediction and optimization models that support core business decisions and processes. They help decision makers define efficient pricing strategies (Wu, Li, & Xu, 2014), estimate market share, determine the optimal pace for product updates (Rusmevichientong, Shen, & Shmoys, 2010), or identify optimal product assortments. Zhao et al. (2015) proposed to exchange utility in price for the utility of entire products to estimate consumers' WTP. Based on experimental data set, they showed how retailers can use these willingness to pay estimates for profit-maximizing pricing decisions. Scholz et al. (2015) proposed a utility-based RS which measures consumer preferences and WTP reliably and at low costs for companies and low cognitive effort for consumers. A number of factors were identified as influential on the customers' WTP for an item, e.g., the item's brand or the item's average rating. Their result showed that the ability to successfully predict consumers' WTP and acceptable prices can lead to significant increase in profitability. However, the impact of such dynamic pricing on long-term customer satisfaction has not been studied.

Attracting customers and increasing profits through price promotions

Price promotions are the daily marketing activities of the competitive B2C market. Determining the best promotion policy is a daunting task that requires balancing the price reduction to attract customers and maintaining a reasonable price to achieve profitability, which can greatly affect the company's profitability and long-term survival. To maximize the profit, Jiang et al.(2015) proposed an analytical model to help e-retailers exploit the potential of online promotion, and to maximize the influence of product recommendation on e-retailer's sales and profits. They argued that RS can and should include pricing decisions, and make use of the intricate complementary and substitute relationship to enhance a firm's profits. Through attractive price discounts, e-retailers can motivate customers to purchase the promoted product, and by way of online RSs, e-retailers can encourage customers to buy non-discounted items. The best promotional effect can be achieved by concurrently optimizing price promotion and product recommendation, because the loss from discount can be compensated for by the gains from the regular items.

The general assumption in the above study is that retailers want to attract customers through discounts on promotional items and then use RS to increase sales of undiscounted items. But in reality, the most relevant products for users may often be different from the products with the most profitable value of suppliers. Based on this, Lu et al. (2014) took into yet another set of additional factors such as saturation effects, capacities, or competition amongst products. The authors furthermore optimized the revenue over a finite time horizon, aiming to find the optimal point in time to recommend certain items. To further investigate the relationship between short-term profit maximization, relevance ranking, and trust, Panniello, Hill, and Gorgoglione (2016) conducted an empirical study and tested different marketing strategies. Their email-based research showed that balancing relevance and profitability lead to higher profits than simple content-based recommendations. This conclusion suggests that the profit-maximizing recommendation does not immediately lead to lower consumer trust.

Enhancing Customer Relationships

In customer relationship management, consumers' retention rates can be a salient determinant to evaluate consumers' long-term performance. In addition, this metric is directly associated with consumers' lifetime monetary value. Park and Han (2013) explored the impact of product category diversity on customer retention rates. Through economic analyses, they found that as the number of purchased product categories increase, customer retention rates dramatically increase, and the effectiveness (e.g., changes in retention rates) from an increase in diversity is larger than the effectiveness from an increase in the number of purchases within the same (single) product category. Moreover, through additional scenario analyses, they also showed that recommending a new category item is much more effective than recommending an existing category item in improving customer retention rates (and therefore long-term profitability).

Due to the virtual nature of e-commerce, thus a consumer may be in an unclear thought process that whether or not he should opt for online shopping. Thus loyalty involves as a major deciding factor if a vendor wants the consumer to buy something from his website. Zhang, Agarwal, and Lucas (2011) used the theoretical framework of the family production function model in the consumer economics literature to explain the mechanism by which personalized recommendations influence customers' loyalty to online retailers. In particular, drawing on the theoretical framework of consumer inferences of marketer motives, Jeong and Lee (2013) compared the effectiveness of different types of RSs in forming favourable consumer attitudes towards an e-commerce website.

RESEARCH ON THE NEGATIVE IMPACTS OF RS

Although RSs have brought a lot of positive effects on consumer decision-making and merchant profitability, some scholars have explored the potential (and possibly unintended) negative effects associated with the recommendation system.

The Effects of RS Bias

The ultimate goal of an online merchant with RSs is to generate more business opportunities by providing consumers with personalized product recommendations. Therefore, merchants do not simply maximize the benefits of consumers in the shopping process, but rather seek to strike a balance between consumers' benefits and business criteria. With such mixed motivations in mind, the merchants may implement RS to provide recommendations that are not solely preference-matched to benefit consumers but instead biased toward its own interests.

Xiao and Benbasat (2018) examined how biased personalized product recommendations influence consumers' decision quality and decision effort when they are shopping online. This study focused on undesirable consequences of PRA use and answered the call that more academic research is needed to explore the dark side of information technology (IT). According to their research, "if the biased personalized recommendations do not result in improving objective decision quality for the consumer, while at the same time these recommendations lead the consumer to believe that her product choice is an optimal one, leading to her continued reliance on the PRA, then unscrupulous online merchants will have a powerful means with which they can influence consumer decision making towards the merchants' own benefits"(p. 2). Xiao and Tan (2012) pointed out that consumers who are sensitized to the double role played by online PRAs, via news stories or warnings issued by consumer organizations, may become hesitant to use the assistance of PRAs when making purchases online, for fear of being exploited by unscrupulous PRA providers (e.g., dishonest online retailers). Such general reluctance not only deprives consumers of the potential benefits offered by PRAs but also makes a mockery of the effort exerted by honest online retailers in implementing PRAs on their websites. However, explicitly telling consumers that potential personalized recommendations are biased will improve their performance in detecting prejudice in personalized recommendations. The most effective mechanism to support consumers in detecting bias is to provide them with warning messages, including suggestions (or tips) for personalized recommendation bias risks, and to emphasize to consumers the potential loss of not following the recommendations (Xiao & Benbasat, 2015).

Fragmentation vs. Homogenization

Some scholars argue that recommender systems can lead to a reduction in sales diversity, as they only reinforce the popularity of already-popular products. Others believe that because of lower search costs, users tend to discover new (or unseen products) and more diverse products by using these systems. What means that RSs will create fragmentation, causing users to have less and less in common with one another or recommenders may do the opposite: recommenders may have homogenizing effects because they share information among users who otherwise would not communicate.

Hosanagar et al. (2013) presented empirical evidence for the debate on whether RSs fragment versus homogenize internet users. In contrast to concerns that users are becoming more fragmented, they found that a network of users becomes more similar to one another after recommendations, as defined by purchase similarity. This increase in commonality occurs for two reasons, which they termed volume and product mix effects. "The volume effect is that consumers simply consume more after personalized recommendations, increasing the chance of having more items in common. The product mix effect is that, conditional on volume, consumers buy a more similar mix of products after recommendations"(p. 1). Bodoff and Ho (2015) extended the prior literature on website personalization by drawing attention to the effects of website personalization on online users' activities on the entire website, not only their response to the personalized recommendations themselves. They examined whether the increase in sampling of personalized items comes at the expense of sampling of other items on the site. In other words, does sampling personalized items increase total sampling activity, or does it cannibalize sampling of other items? In the latter case, there may be no benefit to the website. The research confirmed that personalized recommendations limit the research hypothesis that consumers discover novelty products. And it pointed out that the personalization of the website is not beneficial from every angle. What the website needs to do is how to effectively use the personalized recommendation technology to produce positive effects.

Finally, the work of Adomavicius et al.(2017) suggested that RS has significant side effects on consumer economic behavior, as inaccurate advice may distort the willingness of consumers to pay. Based on portfolio theory, Zhang et al. (2013) suggested that it is sometimes best not to make personalized recommendations for certain users, but only recommend popular ones. Because, in some cases, non-personalized recommendations can provide more relevant (or interesting) items, and personalized techniques may not capture the user's current personal interests and lead to low quality recommendations. In a market where providers compete with each other, Li et al. (2016) found that personalized recommendations may have both positive and negative effects. RSs can increase the market by recommending products to consumers, and may also result in price competition and low profitability of providers.

CONCLUSION AND FUTURE WORK

With the rapid development of the Internet and mobile commerce, many companies have begun to establish their own websites or join third-party platforms to carry out e-commerce and network marketing. But how do you effectively translate customer click-through rates into turnover rates? How to effectively and accurately control corporate marketing costs? In response to this series of problems, many companies have begun to apply digital marketing methods. As a digital marketing technology, RS has strong marketing advantages. It can not only provide consumers with suggestions for products and information, but also simulate sales personal to help customers complete the purchase decision process. RS has attracted more and more researchers' attention in the business value of B2C e-commerce.

First, the premise of personalized recommendation on consumers' purchasing decisions is to attract consumers to use RS. For this reason, scholars have done research on consumer self-factors, system factors and social factors based on the theories of technology acceptance and focused on the issue of consumer's trust in personalized recommendation. As interactive assistant decision-making tools, RSs can reduce the decision-making effort and decision-making time of consumers, increase the input of user information, and thus improve the quality of decision-making. At the same time, with the development of social e-commerce, online consumer reviews of recommended products have become an important source for consumers to make purchases decision.

Second, with the application of big data and artificial intelligence technology, analyzing the actual data of e-commerce transaction activities, including sales data or consumer behavior data, has become a new direction for researchers to further study the business value of RSs to e-commerce market and e-commerce firm. Social e-commerce represented by internet celebrity, micro-business, etc. enables product information to be shared into people's lives through social channels. Consumers access shopping information through social relationship chains and share shopping experiences through social networks. The social media and social network have stimulated scholars to explore the impact of user recommendations and product recommendation networks on product demand and product sales respectively and jointly. The ultimate goal of the company to provide RSs is to make a profit. Therefore, how to attract customers and increase profits by price promotion and estimating consumers' willingness to pay for recommended products are both the focus of future research.

Finally, the application of personalized recommendation technology has been continuously proved by researchers to benefit consumers and business, but its negative effects are less studied. Some scholars believe that the website may provide RS, which may be more in consideration of their own interests, thus resulting in biased personalized recommendations. How to reduce consumers' perception of the RS's deceptiveness and establish more effective guidelines of good business practices online should be the next research directions. In terms of homogenization effects and heterogeneity effects, researchers still have not reached a consensus conclusion. Considering that different recommendation methods, different RS types and consumers' own traits may lead to different research conclusions, we suggest that future research should continue to explore further on the basis of comprehensive consideration of the above factors.

ACKNOWLEDGMENT

This work is partially supported by grant U1711263 of the Natural Science Foundation of China; 2017AA16004 of the Science and Technology Project of Guangxi Province, China.

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(*Full reference list is available upon request from the corresponding author.)