2019 9th International Conference on Education, Management, and Computer (ICEMC 2019)

Factors Influencing the Adoption of Personalized Recommendation: A Literature Review

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Keywords: Personalized recommendation; Adoption theory; Recommendation system

Abstract: With the development of e-commerce, no matter from the technology or consumer demand, personalized recommendation is an important link in the development of e-commerce platform cannot be ignored, because it, as an effective tool to deal with "information overload" problem, has been more and more research and attention. This paper classifies and summarizes personalized recommendation algorithms and current adoption theories in e-commerce environment, and summarizes the advantages and disadvantages of existing algorithms and theories. Personalized recommendation of e-commerce platforms has excellent development prospects, but still needs theoretical innovation in relevant aspects.

1. Introduction

With the wide popularization of computers and the Internet as well as the support and promotion of the government, China's e-commerce market has made a vigorous development, and the market transaction scale is increasingly large. In 2017, the total online shopping consumption accounted for 19.4% of the total retail sales in China.

According to the research report on China mobile e-commerce industry released by iResearch consulting in 2017, China's online shopping market transaction scale was 4.7 trillion yuan (the sum of C2C transaction scale and B2C transaction scale) in 2016.

The number of commodities on major e-commerce platforms has reached an extremely large number. For example, JingDong, as an influential e-commerce platform, had 40.2 million items in 2014, SuNing commerce had no less than 20 million items at the end of 2015, while wal-mart and carrefour had about 60-70 thousand items.

Therefore, under such circumstances, the recommendation system is increasingly valued by e-commerce platforms.

2. Recommendation System Description

2.1 The Development of Recommendation System.

With the development of e-commerce and the sharp increase of commodities on e-commerce platforms, users are in urgent need of finding and finding commodities they need or may be interested in conveniently. In real life, users do not have a clear understanding of their potential needs. If the website can provide users with some goods or services that they may be interested in, it may lead to cross-selling, so the recommendation system is born. In 1992, Goldberg et al. developed the first recommendation system Tapestry [1]. In 1995, Armstrong et al. [2] first proposed the personalized navigation system Web Watcher.

The recommendation system USES the user data collected, including purchase records, browsing records and favorite records, and judges by the similarity of various recommendation algorithms. By recommending products that users may be interested in, it helps users to complete the purchase behavior [3]. Since then, a large number of scholars and e-commerce entrepreneurs have conducted in-depth research on the recommendation system. The research on personalized recommendation

  DOI: 10.25236/icemc.2019.082

mainly focuses on the following aspects: the application of recommendation technology in the recommendation process and the research on recommendation quality. In the research of recommendation technology, Cataldo et al. [4] established the information base based on the user's behavior, calculated the similarity between the goods and the information base, classified the goods according to their similarity, and finally generated the recommendation results. Goldberg et al. [1] proposed the collaborative filtering algorithm, which used the evaluation of users with similar or same interests on a certain product to simply estimate the current user's preference for the product. Professor Sarwar et al. [5] of Lens Group further extended the collaborative filtering technology, and proposed a project-based collaborative filtering algorithm to improve the recommendation efficiency by calculating the similarity between projects, so as to replace the similarity between users. Afterwards, in order to improve the accuracy of the recommendation results, solve the problems of data sparsity and "cold start" in the application process, many improvements were proposed to the project-based collaborative filtering algorithm. Chaiwat et al. [6] improved the similarity of its neighborhood by adding items. Deng ailin et al. [7] introduced the scoring mechanism into the recommendation algorithm on the basis of collaborative filtering, thus improving the recommendation effect. The effects of these improvements have been well demonstrated in different areas. Association rules, cluster analysis, bayes and other data mining techniques have been widely used in personalized recommendation. Mobasher et al. [8] proposed the concept of site, and captured site semantics by integrating site content data to generate various recommendation rules. Mooney et al. [9] applied the bayesian classifier in the paper on recommendation algorithm published in 2009, and proposed an algorithm based on text content classification. The user click data is used as input of the recommendation model, and the grammar, semantics and pragmatics are taken into full consideration to establish the framework of the recommendation system [10].

In terms of research on recommendation quality and real-time performance, Sarwar et al. (2000) [11] used singular value decomposition to reduce the dimension of the project, which solved the problem of low recommendation quality caused by sparse data. With the development of e-commerce platform and the continuous optimization of personalized recommendation system, higher requirements are put forward for the expansion ability and real-time performance of the recommendation system. Shahabi et al. (2001) [12] designed a recommendation framework, including offline training and online use, and improved the quality and real-time performance of recommendation results. IBM laboratory USES TAG technology to improve the quality of personalized recommendation [13].

2.2 Types of Personalized Recommendations.

Personalized recommendation is a kind of personalized service that is available in almost all e-commerce platforms. It is based on the purchase history and browsing items of the users, the platform speculates the target demand and gives commodities or services similar to their preferences.

In a word, personalized recommendation is the matching of commodities and users' needs.

Personalized recommendation can be divided into different types through algorithms, concepts and ideas.

It can also be divided into recommendations based on explicit feedback and recommendations based on implicit feedback, depending on the data type used to generate the recommendations.

According to the algorithm used, it can be divided into content-based recommendation, collaborative filtering recommendation and mixed recommendation.

Personalized recommendations based on explicit feedback generally require users to provide some information of their own.

What type of guy (or girl) you are, etc. Preference information or personal information, and then will produce personalized recommendation information.

Personalized recommendation based on implicit feedback generally means that consumers will unconsciously record their behaviors and preferences, and it does not require users to provide certain information to generate personalized recommendation.

Therefore, compared with explicit feedback, implicit recommendation is more accepted by various e-commerce platforms, while implicit recommendation is more applied to social software and video software.

Content-based personalized recommendation is based on the product characteristics and the user's shopping history for feedback, and does not rely on the user's other preference information or personal information.

This type of recommendation algorithm will look for items with similar attributes to the items that the user has purchased or liked.

The general idea is as follows: first, build the user's document according to the user's browsing record or purchase history, then compare the similarity between the product and the user's document, and finally recommend the product with the highest similarity to the user's document [14].

The collaborative filtering algorithm does not analyze the content or features of the product, but recommends the product to the current user based on the rating or implicit data of other users.

The algorithm based on collaborative filtering is also usually the most favored by e-commerce platforms, and its essence is to recommend products favored by other users [15].

There are also memory-based collaborative filters that predict and recommend by noting similarities between users or items.

Among them, collaborative filtering based on user neighborhood and item neighborhood can also be divided according to different goals.

User-based collaborative filtering, on the other hand, is based on the similarity of different users in certain behaviors or preferences, and then recommend products that they may like but have not yet noticed.

Project-based collaborative filtering is that after the user selects a certain item, the system will recommend the item with similarity or complementarity to the user.

Model-based collaborative filtering recommendation establishes consumer preference model and generates personalized recommendation through methods such as linear regression.

Content-based and collaborative filter-based recommendations have some drawbacks, such as the "cold start" problem and the incompatibility of complex products with more features [16-17].

The recommendation algorithm based on bipartite graph was first proposed by Aggarwal in 1999 [18]. This kind of algorithm is more concerned with the choice of a certain product rather than the form of the product.

The user - product bipartite graph model is established by user's choice of product.

The core of the algorithm based on association rules is the behavior of users, which can extract potentially useful association rules from a large amount of data and recommend items of interest to users based on these associations.

Scholars Agrawal and Swami first proposed the algorithm concept based on association rules, and the first association rule algorithm is the classical Apriori algorithm [19].

Recommendation algorithms based on social networks rely on the data of social networks to capture the information of users' interests, preferences and friends, and provide personalized product recommendations for users based on these data.

Social networks bring together people from different fields, occupations, regions and other characteristics, which greatly enriches people's circle of friends and also drives potential business opportunities in regional social network marketing [20].

To sum up, the advantages of collaborative filtering are :(1) do not need to consider the content of the recommended project;

(2) effectively dealt with the "cold start" problem;

(3) the technology is mature, so it is the most commonly used recommendation algorithm for e-commerce platforms at the present stage.

Table 1 Recommendation algorithm technology comparison

Recommended Algorithm	Major Advantage	Major Defect
Content-Based Recommendations	High degree of personalization high degree of automation The results are intuitive and easy to interpret	Not suitable for complex commodities There is a "cold start" problem
Collaborative Filtering Recommendation	High degree of personalization high degree of automation Effective response to "cold start" Mature technology, easy to achieve	Sparsity problem Content restrictions
Hybrid Recommendation	High degree of personalization High degree of automation Effective response to "cold start" Improve recommendation accuracy	Finite content analysis The execution efficiency is lower than single algorithm Technical implementation is difficult
Recommendation Based on Bipartite Graph	Recommended content is not limited The recommendations are diverse	Limited by new users, new products Without considering the difference in user rating, the recommendation quality and the degree of personalization are low
Recommendation Based on Association Rules	Find new interests No domain knowledge required	The establishment of association is time-consuming and difficult to extract Low degree of personalization
Recommendations Based on Social Networks	Using friends to make recommendations increases users' trust in the recommendation results	It is difficult to get the information of users' friends in the real system

Collaborative filtering recommendation has some advantages over other recommendation technologies, such as:

1) The types of recommended objects are not limited.

Since collaborative filtering generates recommendations based on the preferences of similar users, it is important to find other users with similar preferences to the target user, rather than the type of recommendation item. Therefore, collaborative filtering applies to a relatively wide range of recommended items.

2) Effectively dealt with the "cold start" problem.

Collaborative filtering recommendations do not take into account the relevance of recommendations to users. And the recommendation project does not necessarily have the user's historical data and behavior, which will be helpful for mining potential users, to achieve the upgrade of the recommendation.

3) The technology is easy to implement.

The user preference information is easy to collect on the e-commerce platform, the program is not complex and has good scalability, so the implementation of the whole collaborative filtering system is relatively easy.

3. Introduction to Adoption Theory

3.1 Theory of Rational Behavior.

In terms of the research on the theory of rational behavior, Fishbein and Ajzen proposed the theory of rational behavior in 1975, which is mainly used to analyze the influence of attitude on individual behavior.

This theory holds that individual behavior can be determined by behavior intention to some extent, and individual behavior intention is also influenced by behavior attitude and subjective norms. Domestic and foreign researches on the prediction of individual behavioral tendency by rational behavior theory have been verified. Xiaobing Song et al. established the user's brand purchase intention model, and tested the validity of the model based on the actual purchase situation, proving that in the purchase behavior, attitude and subjective norms are the direct influencing factors, and the influence of subjective norms is stronger than attitude. Xiuzhen Feng et al. constructed a model of information sharing behavior, which has a significant effect on the prediction of members' information sharing behavior. Many researches have proved that the theory of rational behavior can effectively predict users' use behavior of information system. Yaobin Lu et al. proposed to add mediating variables, including attitude and subjective norms, and other influencing factors indirectly influence behaviors through mediating variables. However, the application of this theory is limited by the limitations of resources and the fact that individuals' wishes sometimes cannot control their own behaviors.

In order to expand the application scope of rational behavior theory, Ajzen added perceived behavior control into the original theoretical framework, and then proposed planned behavior theory.

Figure. 1 TRA Model

3.2 Theory of Planned Behavior.

The theoretical study of planned behavior was formally proposed by Ajzen in 1991. He believed that intention is determined by individual's attitude, subjective norms and perceived behavior control, and behavior is also directly affected by perceived behavior control.

The theory of planned behavior has been successfully applied widely and has a good interpretation in improving the interpretation and prediction of behaviors, but there are few studies on the theory of planned behavior in China. Pavlou et al. established the user e-commerce adoption model on the basis of this theory, and verified the model through empirical research. Under the framework of planned behavior theory, the problem that rational behavior model can't consider environment and resource constraints is solved by combining trust factor and information technology adoption factor. Yanli Zhao et al. analyzed users' mobile payment behavior and explored the influencing factors of users' mobile payment behavior.

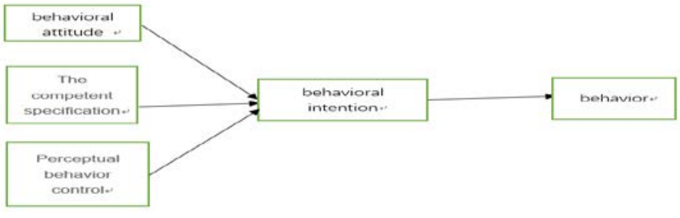

Figure. 2 TPB Model

3.3 Technology Acceptance Model.

The technology acceptance model was first proposed by Davis in 1989 when he began to study users' adoption of information systems.

According to the user's adoption behavior of the system, this model believes that the adoption of the system is determined by the user's usage intention, and the personal attitude and perceived usefulness of using the system will affect the user's usage intention.

However, this model only considers the two main variables of usefulness and usability, so it limits the scope of the model.

Venkatesh and Davis extended the technology acceptance model to explore other influencing factors besides perceived usefulness and perceived ease of use in the technology acceptance model.

Two variables, social influence process and cognitive tool process, are added into the technology acceptance model.

The external variables indirectly affect users' intention and behavior to adopt information technology through perceived usefulness and perceived ease of use.

At the same time, Davis systematically summarized the external variables acting on the model in the empirical study, and eliminated the intermediary variable "attitude" which played a very limited role.

The availability of an extended version of the technology acceptance model is significantly expanded.

Since then, many scholars have improved the technology acceptance model to varying degrees, and some scholars have added subjective criteria and social influencing factors into the technology acceptance model.

Lin (2009), such as electronic database in the library on the interaction design of users for the students to build technology acceptance model, and carries on the empirical analysis and test, the purpose is to study the influence the behavior of students accept useful perception, ease of use, the characteristics of the system and user variables, Kenneth (2005) using the technology acceptance model to study the Singapore market user acceptance of mobile commerce.

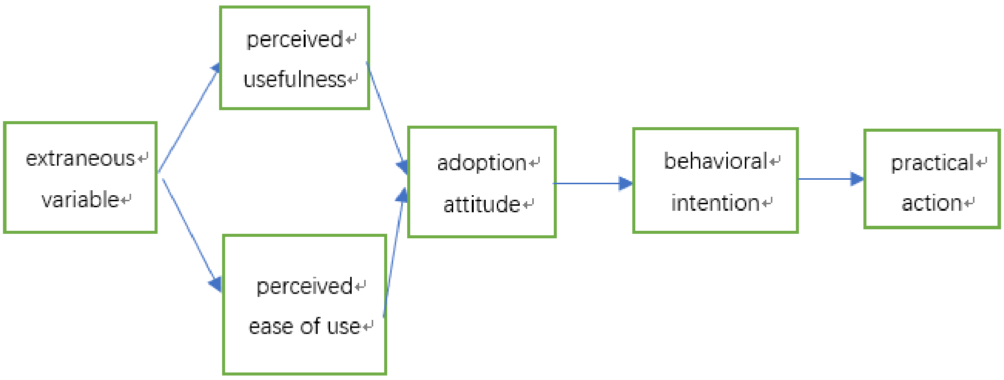

Figure. 3 TAM Model

3.4 SOR.

Many studies have shown that SOR model can effectively explain the user's psychology and behavior towards the surrounding environment in business activities.

The s-o-r model starts with psychology.

This model thinks that when users encounter a Stimulus (Stimulus, S), their Organism (O) also changes, leading to their Response to the Stimulus (Response, R). Subsequently, Donovan R J et al. applied the s-o-r model to sales, believing that the sales environment will stimulate consumers' pleasure, arousal and control, and affect their proximity or avoidance behavior. With the development of e-commerce, more scholars have used the s-o-r model to describe users' social business behaviors in recent years.

In the existing relevant researches, the mentioned stimulating factors include text features, technical factors, social factors, etc. Organism includes emotion, attitude, etc.; Responses include purchase intention, use intention, and sharing intention.

It can be seen that there are not many researches on interpersonal interaction, social support and trust.

Liang T et al. believe that interpersonal interaction and social support are important factors to stimulate the behavior of social business users, but they have not attracted enough attention from scholars.

However, Hajli M N proposed that trust significantly affects the purchase intention of social business users. However, the existing studies mainly regard trust as a whole, which is mainly subdivided and discussed its internal mechanism of action.

In addition, in the context of social business, users' shopping decisions are mostly based on the information provided by others, while there are few studies on the sharing behavior of social business.

4. Previous Research Results of Personalized Recommendation

A. A. Shaikh et al., based on the technology acceptance model, revealed that perceived usefulness and attitude are important factors affecting the adoption behavior of mobile Banks. Yue Chen et al. studied the risk model, in which the risk of online shopping mode and its impact on users' behavioral intention were analyzed in detail.

Domestic scholars also did some research on the influence factors of user adoption behavior, for example: Shuiqing Yang etc. based on the scenario study proved that the perception of mobility significant positive influence on the user's mobile Internet adoption intention, it also illustrates the mobile technology has not affected by the nature of time and space limit, this is also the key factors influencing the user adoption behavior.

Weijun Wang et al. believe that users' perception of the performance of recommendation technology, subjective norms and users' own innovation all affect their acceptance and adoption of recommended products or services. Therefore, it is necessary to analyze how to improve the adoption intention of recommendation technology from the perspective of user experience perception.

Xiwei Wang et al. showed that the adoption attitude of group purchase APP has a positive impact on the adoption behavior, and the influence intensity of information ecological factors on the adoption attitude of APP is, in turn, information person, information technology, information environment and information, and the influence of each factor on the adoption attitude has a certain co-variation relationship.

Based on the technology acceptance model, Xinhua Bi, Wan Su et al. discussed the influence of users' perceived usefulness and perceived ease of use on their behavioral intention in combination with the characteristics of mobile commerce.

Recent advances in recommendation algorithms have focused on computer science, which focuses on predicting and generating consumer preferences for goods.

Through complex models and algorithms to provide users with more suitable product recommendations. Content-based recommendations are often adopted for news, microblog and web pages, among which clustering analysis method and Bayesian model are used. One advantage of content-based recommendation is that it does not require the user to have any previous behavior record of a certain item or whether an item has ever been used by the user. In other words, it has a better response strategy to the "cold start" problem.

The algorithms based on collaborative filtering are commonly used "neighbor method", data dimensionality reduction and other methods.

In recent years, some new methods that can be applied have also been proposed, and the analysis based on scenario clustering is also a commonly used method for collaborative filtering.

There is also an analysis of the influencing factors of the recommendation algorithm through user, project, scenario and other dimensions. Collaborative filtering based on temporal behavior is a method to model temporal behavior among users (products). Based on this method, the neighbor set that has the greatest influence on the current user (product) can be found. Collaborative filtering based on user similarity defines attribute similarity in social networks, and provides recommendation quality and user satisfaction evaluation methods. There are also new product recommendations based on consumer psychology and behavior.

5. Conclusion

Through the review of the above literature, it can be seen that the influencing factors for consumers to adopt personalized recommendation have extended to various fields and become the hot research topic at present.

The study of personalized recommendation, particularly prominent practical significance to China, because China has a huge consumer groups, on the other hand is due to consumer adoption intention of personalized recommendation is decided by many aspects, so in addition to the production of recommendation system itself also need to consider include social and psychological impact on consumers. It is also a serious challenge for entrepreneurs and researchers.

In the face of this situation, domestic scholars should conduct in-depth research on relevant influencing factors. However, the reality is that the mainstream framework of consumer adoption model adopted by domestic scholars is still mostly dominated by American scholars, and domestic scholars have not put forward a better research model. In addition, for goods consumed by consumers, most researchers tend to study the recommendation of a single type of goods, while the recommendation of multiple types of goods is relatively rare.

In addition, with the development of new retail and gradually community-based e-commerce platform (such as box and horse fresh food, etc.), the personalized recommendation of consumers in the future will develop towards the direction of community, which will make factors such as the social relationship between people become the influencing factors for the adoption of personalized recommendation and the development direction of the recommendation system.

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