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The Impact of Algorithmic Product Recommendation on Consumers' Impulse Purchase Intention

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Abstract: With the development of the Internet and e-commerce, more and more information is presented in the public eye. Due to the limited human experience and time, the efficiency of processing massive amounts of information often decreases significantly. Algorithm based product recommendation is a recommendation system based on data mining and machine learning technology. It recommends products that users may be interested in by analyzing their historical behavior, personal preferences, and other factors. Algorithm product recommendation is generated to solve the problem of consumers facing difficulty in selecting a large number of products. An e-commerce website needs to recommend products that users may be interested in, but due to the large number of products, it is difficult to meet the personalized needs of each user. By using algorithmic product recommendation technology, e-commerce websites can recommend products that users may be interested in based on their historical behavior and personal preferences. This not only improves the shopping experience of users, but also increases the sales volume of e-commerce websites.

Keywords: Algorithm product recommendation, Accuracy, Perceived practical value.

1. Introduction

This article explores the impact of algorithmic product recommendations on consumers' impulse purchase intention based on the accuracy and diversity of user perceived recommendations, as well as the mechanism of perceived value in it. Through empirical research on 97 survey questionnaire samples, a combination of quantitative and qualitative research methods was used. The research process is divided into two parts. The first part is to explore the qualitative research, based on the impact of the accuracy and diversity of consumer perceived recommendations on their impulse purchase intention in real situations. The second part, based on the research results, elucidates the role of mediation mechanisms in addressing the main research issues of this article.

In the past, consumers could only understand product information through advertising, promotions, and other means, and choosing products required a lot of time and effort. With the development of the Internet and e-commerce, more and more products are being put on the shelves, and consumers are also facing an increasing number of products. Therefore, algorithmic product recommendation has emerged. By analyzing user historical behavior, interests, and other information, personalized product recommendations are provided to help users quickly find the products they want, thereby improving their shopping experience.

2. Literature Review

Algorithm product recommendation is generated to solve information overload and improve user purchasing experience. In the era of the Internet, consumers are facing a massive selection of products, making it difficult to find the products they are truly interested in. In order to solve this problem, recommendation systems have emerged. Algorithm product recommendation analyzes users' historical behavior and interest preferences, constructs user profiles, and utilizes algorithm technologies such as machine learning and collaborative filtering to associate users with similar interests or products, thereby providing personalized product recommendations to users. With the rapid development of the Internet era and the continuous application of high-tech such as artificial intelligence, while meeting the diverse preferences of consumers in the market, problems such as data surplus and information overload have emerged. Traditional e-commerce marketing recommendation systems typically utilize consumers' historical consumption and browsing information on current platform websites to further recommend personalized products and services. With the continuous application of big data and artificial intelligence technologies, consumer preference information on other platforms has also been valued by major e-commerce platforms and to provide a more convenient and comfortable consumption experience for platform users.

At present, many scholars in the academic community have paid attention to algorithmic product recommendation. Some scholars have studied the characteristics and application levels of algorithmic recommendation, and believe that e-commerce platform enterprises can achieve precise marketing through personalized intelligent recommendation systems. On the one hand, it can improve the efficiency of platform website information data processing and consumer purchase intention; On the other hand, it can improve consumers' satisfaction and loyalty to the platform website [1]. Existing research has shownthat the accuracy of algorithmic product recommendations can have a significant impact on consumers' perceived value and purchase intention, such as influencing consumers' perceived value, purchase intention, and psychological activities of online shopping [2]. Due to the fact that the essence of algorithm recommendation is to push products that meet the interests or needs of users, some scholarsbelieve that the prerequisite for implementing personalized recommendation is to obtain user preferences, and the completeness of user attributes is also a key factor.Lacking the psychological impact process of the accuracy and diversity of user perceived recommendations on consumers' online impulse purchase intention. The accuracy of algorithmic product recommendations directly affects consumers' purchasing intentions. If the recommendation system can accurately understand the interests and needs of users and provide personalized recommendations that meet their expectations, consumers will be more inclined to purchase the recommended products [3].

When applying algorithm recommendations, one should consider: accuracy (recommendation systems need to continuously learn and optimize to improve the accuracy of recommendations to meet users' personalized needs.) Diversity (recommendation systems should consider users' diverse interests, avoid excessive reliance on popular products, and provide users with more choices.)

3. Research Meaning

3.1. Theoretical significance

Through product recommendation, personalized product recommendation services can be provided based on users' personal characteristics and behavior patterns to meet their personalized needs. Among the vast amount of product information, algorithmic product recommendation can filter and filter users' information, improve user search efficiency, improve their shopping experience, and enhance their satisfaction and loyalty to the platform.

3.2. Practical significance

Through precise product recommendations, the exposure and click through rate of products can be increased, user willingness and purchase volume can be increased, thereby improving sales efficiency. By analyzing and mining user behavior data, user preferences and demand information can be obtained, providing data support for enterprise product development, marketing, and operational decisions. Enterprises can establish a good brand image, enhance their competitive advantage, and attract more users and potential customers. The shopping experience of users reduces their search.

By using algorithmic product recommendation technology, e-commerce websites can recommend products that users may be interested in based on their historical behavior and personal preferences. This not only improves the shopping experience of users, but also increases the sales volume of e-commerce websites.

4. Research Contents

4.1. Research Purpose

The research aim is to provide consumers with more accurate personalized goods and services, provide more convenient and comfortable consumption experiences for platform users, and increase business revenue to achieve win-win results.

4.2. Research questions

4.2.1. Is the accuracy and diversity of perceived recommendations a key factor affecting consumers' impulse buying

Research has shown that the online comment content of algorithmic product recommendations and the arrangement and presentation of information can affect consumers' purchasing behavior [4,5]. Recommendation systems can meet consumers' psychological needs for efficiency, convenience, safety, and reliability, thereby positively influencing their purchasing intention.

The stimulus response theory suggests that human behavior is caused by the environment and external stimuli, and behavior is a direct response to external stimuli. This means that human behavior is passive, and external stimuli are the dominant factor. For consumers, the information recommendations, system interactions, and community influences they encounter on e-commerce platforms are all external environmental

During the shopping process on e-commerce platform websites, in addition to searching and browsing for planned purchases, consumers often purchase products that differ from their expected shopping list, resulting in impulsive purchasing intentions.

4.2.2. The process of perceived use value of algorithmic product recommendations affecting consumer psychology

Perceived use value refers to the value that a person feels when perceiving and using a product or service. This includes the functionality, performance, appearance, quality, and other aspects of a product or service, as well as their degree of satisfaction with the individual needs and preferences of users.

Perceived usage value is an important indicator for users to evaluate the value of a product or service. The higher the perceived value of a product or service, the more satisfied users are with it, and the more likely they are to purchase and use it. Therefore, enterprises need to pay attention to the perceived use value of products and improve their functionality, performance, and quality to enhance their perceived use value.

In addition, intelligent marketing services such as reasonable information organization and appropriate recommendation intensity can bring consumers a good sense of platform use, enhance the perceived ease of use and usefulness of personalized intelligent recommendation systems, and thus generate perceived practical value for consumers and stimulate their online impulse purchase intention. Therefore, the following assumptions are proposed:

Perceived practical value plays a mediating role in the impact of algorithmic product recommendations on consumers' online impulse buying intentions.

5. Research Design

5.1. Variable Measurement Description

The key variables involved in this study are the accuracy, diversity, perceived practical value, and consumer impulse buying willingness of e-commerce platform algorithm product recommendation information. To improve the credibility and effectiveness of the questionnaire, the measurement items refer to mature scales in existing research, and combine the characteristics of e-commerce platform algorithm intelligent product recommendation with consumer shopping environment to make reasonable modifications and adjustments to some items. The accuracy of e-commerce platform algorithm product recommendation information related scales for measurement, with a total of 4 items [6]. The diversity of product recommendation information in e-commerce platform algorithmsrelated scales for measurement, with a total of 4 items [6]. Perceived practical value is measured using relevant scale, with a total of 4 items [7]. Consumers' online impulse purchase intention was measured using the relevant scale, consisting of 4 items [8,9].

5.2. Survey questionnaire design

Based on the above basic variable measurements, a survey questionnaire was designed using a questionnaire star. The scale ranges from "strongly disagree" to "strongly agree" based on the perceived level of different respondents

The scores of "uncertain", "basically agree", and "strongly agree" are given 1-5 points for scoring. The higher the score given by the respondents, the higher the perceived level.

6. Experimental Research Results and Analysis

6.1. Reliability and Validity Testing of the Questionnaire

To ensure reliability, the reliability of the questionnaire is tested using Cronbach's Alpha (a value): the closer the a value is to 1, the higher the reliability. The KMO (Kaiser Meyer Olkin) index and Bartlett index can be used to test the validity of the questionnaire. The reliability and validity of the questionnaire were tested by combining these three indicators, and the test results are shown in Table 1.

Table 1. Perceived Recommendation Accuracy and Diversity Scale

reliability		validity		
variable	Cronbach αcoefficient	KMO value	Bartlett Sphericity inspection	
			Approximate Chi Square Value	significant value
Perceived accuracy of recommendations	0.896	0.765	259.094	0.000
Perceived diversity of recommendations	0.850	0.794	171.84	0.000
Perceived Practical Value	0.812	0.796	121.769	0.000
User impulse purchase intention	0.862	0.812	180.222	0.000

From Table 1, it can be seen that the reliability analysis coefficients of the variables are all above 0.8, which is greater than the critical value of 0.7, indicating that the questionnaire has high reliability. In terms of validity, the KMO values of all variables are above 0.7, among which the KMO value of impulse purchase intention is 0.862, and the accompanying probability value of Bartlett's spherical test is less than the significance level of 0.01, indicating the validity of the questionnaire.

6.2. Correlation analysis

Correlation analysis mainly analyzes the relationship between variables, such as whether there is a relationship between the accuracy of algorithmic product recommendation information and consumer impulse purchase intention, the diversity of algorithmic product recommendation information and consumer impulse purchase intention, and if there is a correlation, describe the degree of correlation. Correlation coefficient is used to represent the relationship between analysis items. When using the spss 22.0 tool for analysis, this article uses Pearson correlation number. In this empirical analysis, the relevant analysis mainly includes three steps:

Firstly, determine whether there is a significant correlation between the relevant relationships. From Table 2, it can be seen that there is a correlation between the accuracy of algorithmic product recommendation information, the diversity of algorithmic product recommendation information, and consumers' impulse purchase intention.

Secondly, determine whether the relationship is positively or negatively correlated. From the analysis results, it can be seen that there is a positive correlation between the accuracy and diversity of algorithm product recommendation information and consumer purchase intention.

Thirdly, judge the closeness of the relationship. Table 2 indicates that the Pearson correlation coefficient between the accuracy of algorithm product recommendation information and impulse purchase intention is 0.748, and the Pearson correlation coefficient between the diversity of algorithm product recommendation information and purchase intention is 0.796. Therefore, the accuracy and diversity of algorithmic product recommendation information are closely related to impulse buying intention.

Table 2. A Scale of Consumer Impulsive Purchase Intention

		Consumer impulse buying willingness
Perceived accuracy of recommendations	correlation coefficient	0.748
	p value	0.000
Perceived diversity of recommendations	correlation coefficient	0.796
	p value	0.000

6.3. Regression analysis

This study uses multiple linear regression analysis to analyze the impact of the characteristics of algorithmic product recommendation information on consumer purchase intention. The results are shown in Table 3. From the analysis results model shown in Table 3, it can be seen that the accuracy of algorithmic product recommendation information is significantly correlated with consumer impulse purchase intention ($P<0.01$) and has a positive impact; the diversity of algorithmic product recommendation information is significantly correlated with consumer impulse purchase intention ($P<0.01$) and has a positive impact.

Table 3. Linear regression analysis results

	Non standardized coefficient		Standardized Coefficient	t	p
	B	standard error	$Beta$		
constant	1.050	0.226	-	4.652	0.000**
Perceived accuracy of recommendations	0.286	0.072	0.345	3.961	0.000**
Perceived diversity of recommendations	0.486	0.079	0.538	6.166	0.000**
R^2	0.686				
$adjustR^2$	0.679				
F	F (2,94)=102.695,p=0.000				
D-Wvalue	2.139				

Dependent variable: Consumer impulse purchase intention

* p<0.05 ** p<0.01

6.4. Mediation effect test

When considering the influence of the independent variables "accuracy of algorithm product recommendation information (X1)" and "diversity of algorithm product recommendation information (X2)" on the dependent variable "consumer impulse purchase intention (Y)", if the influence variable "perceived practical value (M)" is used to influence "consumer impulse purchase intention," perceived practical value "is called the intermediary variable. In order to test the mediating effect of perceived practical value on consumers' online impulse purchase intention, Bootstrap analysis method was used to test the mediating effect. The test results are shown in Table 4. From Table 4, it can be seen that the mediation effect of the accuracy of algorithm product recommendation information on consumers' online impulse purchase intention through perceived practical value is 0.114, with a confidence interval of [0.046, 0.269], excluding a value of 0. This indicates that the mediation effect of perceived practical value on the accuracy of algorithm product recommendation information on consumers' online impulse purchase intention; The mediating effect of the diversity of algorithmic product recommendation information on consumers' online impulse purchase intention through perceived practical value is 0.279, with a confidence interval of [0.080, 0.654] and does not include a value of 0, indicating the mediating effect of the diversity of algorithmic product recommendation information on consumers' online impulse purchase intention through perceived practical value.

Table 4. Mediation Test Results

term	a*b Mediation effect value	a*b (Boot SE)	a*b (z value)	a*b (p value)	a*b (95% BootCI)	c' Direct effect	Inspection conclusion
X1=>M=>Y	0.114	0.057	2.017	0.044	0.046 ~ 0.269	0.172*	partial mediation
X2=>M=>Y	0.279	0.150	1.864	0.062	0.080 ~ 0.654	0.207*	partial mediation

* p<0.05 ** p<0.01

Bootstrap type: percentile bootstrap method

7. Conclusion

This study used reliability testing, validity testing, Pearson correlation coefficient of correlation analysis, regression analysis, and mediation effect testing to determine that the correlation between the diversity of algorithm product recommendation information and purchase intention is greater than the correlation between the accuracy of algorithm product recommendation information and purchase intention. We have verified that diversity and accuracy are positively correlated with impulse purchase intention, and that perceived utility value plays a mediating role in the relationship between algorithmic product recommendation and impulse purchase intention.

This study found that the diversity of algorithmic product recommendations can better encourage consumers to make impulsive purchases. Perceived practical value serves as an intermediary variable to strengthen the impact between the two, providing users with better recommendation content and more convenient information assistance, stimulating their curiosity and exploration, and thus promoting consumption.

Through diversified recommendation algorithms, users can be exposed to different types of products, allowing them to discover more products that meet their interests and needs, improving user experience and satisfaction. At the same time, it can help enterprises expand market share and increase sales. Enable more users to understand different aspects of the brand and different types of products, and improve brand awareness and exposure.

Secondly, perceived usage value is also an important indicator for users to evaluate the value of a product or service. The higher the perceived value of a product or service, the more satisfied users are with it, and the more likely they are to purchase and use it. Therefore, enterprises need to pay attention to the perceived use value of products and improve their functional performance and quality to enhance their perceived use value.

8. Future Outlook

With the continuous development of technology, the accuracy and diversity of algorithmic product recommendations are also being improved and improved. Future algorithmic product recommendations will become more intelligent and personalized, providing more accurate recommendation services. Secondly, future algorithmic product recommendations will be more cross platform, enabling cross domain users to utilize the interaction between the network and users on different platforms and domains to provide recommendation services. At the same time, the continuous refinement of algorithms may also bring more challenges and opportunities. For example, protection of privacy and data security. Therefore, when applying algorithm recommendation technology, it is necessary to carefully consider its potential negative impact and take corresponding measures to ensure user interests and safety.

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