ISSN 2616-5902 Vol. 8, Issue 9: 99-110, DOI: 10.25236/AJBM.2026.080912

Effects of Personalized Product Recommendations on Online Buyers' Purchasing Behavior in China

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Abstract: *Now that e-commerce coverage has been expanding, figuring out how personalized recommendations affect consumers' purchasing decisions is important for businesses that want to adjust their marketing strategies. This article focuses on the actual changes in personalized product recommendations, and what role these recommendations will bring to the purchase behavior of online consumers in China. The purpose of this paper is to analyze the impact of personalized recommendations on purchasing decisions, while examining the role of different demographic characteristics, and to find out the most obvious types of recommendations for actual effects. The final results show that personalized product recommendations have a great impact on purchasing behavior, and "Recently Viewed" is the most prominent. Among the demographic features, gender and certain income levels are significantly associated with purchasing behavior, while age and education show no significant effects.*

Keywords: *Personalized product recommendations, Online buyers, Purchasing behavior*

1. Introduction

In recent years, the operating model and trading pattern of the entire retail sector in China have undergone great changes, and the core reason for this change is that various types of e-commerce platforms have ushered in exponential growth. Now there have been a lot of different positioning, different service direction of the e-commerce platforms, such as Taobao, Tmall, Jingdong, Pinduoduo, Meituan. According to the latest statistics in China Internet Center, the total number of domestic users participating in online shopping has reached 850 million, which accounts for nearly 80% of all Internet users. These e-commerce platforms have indeed brought shopping conveniences that were previously unimaginable to consumers, and also allowed consumers to choose a lot more goods and services than before.

The core element that can make these platforms gain so many user-like and market success is the personalized product recommendation system on which the platform is equipped. The recommendation system uses a number of complex algorithms that have been verified repeatedly, and continues to analyze the user's browsing history and daily consumption preferences, then finally pushes the appropriate personalized content for each user's different needs. The role of personalized product recommendations is much larger than those ordinary unified recommendations on the platform, which play a key role in slowly shaping the process of consumer purchasing decisions, and will also greatly affect the user's complete online shopping experience. Figuring out what kind of impact personalized product recommendations have on online buyers' purchasing behavior has become increasingly important in China, a country with a high market activity.

China itself is the world's largest e-commerce market, and now the speed of various related technology breakthroughs is very fast, consumer preferences have been changing, and the consumption habits of people in different regions have their own characteristics. To better understand the operation of this complex market, it is necessary first to explore in detail how these tailored recommendations affect consumer behavior, and to explore the role of different demographic characteristics in consumers' response to personalized product recommendations.

As a result, this study is aimed to investigate the effects of personalized product recommendations on the purchasing behavior of online shoppers in China, and to make up for the blank parts that have

ISSN 2616-5902 Vol. 8, Issue 9: 99-110, DOI: 10.25236/AJBM.2026.080912

not been covered in the relevant research literature. The central question of the study is to examine the relationship between such tailored recommendations and purchasing decisions, and to assess the role of different demographic factors in purchasing behavior. The research first collated the basic information of the respondents who participated in the survey, and made detailed statistical classification of everyone's age, gender and the distribution of monthly disposable income, and also analyzed the effects of these demographic variables and personalized recommendations on consumer purchasing behavior. Finally, this study compared different types of personalized product recommendations to identify which of the most obvious role in domestic online consumer purchasing behavior. Through this survey, this article hopes to clarify the relationship between tailored recommendations and consumer behavior, and bring valuable reference content to the actual operation of related enterprises and academic field.

2. Literature Review

Personalized product recommendations are now in the relevant research areas of e-commerce, and the reason why these recommendation systems are highlighted is mainly because they can affect the shopping choices of ordinary consumers and play a key role in the process of platform sales growth. Most of recommendation systems utilize mature algorithms and machine learning related technologies. They initially process a large number of various types of user behavior data, and then combine these data to generate exclusive recommendation content that fit the user's preferences, the ultimate goal is to let the user in the platform shopping experience better, can also make the platform's overall conversion rate improved. This section reviews relevant literature on personalized recommendations and their effects on online buyers' purchasing behavior in the context of China's e-commerce market.

2.1. The Emergence of Personalized Recommendations

The continuous maturity of e-commerce enables all kinds of comprehensive services to land. These services include online shopping and online payment that everyone is familiar with, and the platform by providing transaction integrity, universality and convenience such as the core attributes, can bring practical benefits to merchants and consumers at the same time. Now that the number of various online stores is steep growing and the product information on the platform is more complicated, buyers are often dazzled by substantial amount of choices when browsing goods, and easily encounter the situation commonly known as “information overload”.

As a consequence, many consumers can not clearly and effectively express their real needs, when browsing the massive amount of goods related information, which makes their search costs a big increase. Against this backdrop, the personalized recommendation system has slowly developed to deal with these practical problems. The personalized recommendation system first analyzes the personal information of consumers, shopping behavior and daily preferences, and then target to consumers to recommend various products that they are likely to be interested in. This effective and convenient service eliminates the process of consumers spending a lot of time selecting goods, just in line with the actual needs of consumers for shopping efficiency, which can also improve the satisfaction of consumers' online shopping, and can also drive the overall purchase rate of the platform. Now the mainstream online shopping platform has begun to use this kind of recommendation system to rely on it to improve their own quality of service.

2.2. Personalized Recommendation Algorithms

The recommendation systems are a type of program that actively pushes users with content or goods that are likely to be of interest to users. By comprehensively analyzing the user's past purchase records, stored in the platform's favorites, daily browsing traces and other types of interactive behavior data, these systems push products that are more tailored to the user's personal preferences based on the results of the analysis (Elison et al., 2007). There are many types of technologies used in the recommendation system, and the more common types of collaborative filtering, content-based filtering, and model-based recommendations are used. In practice, most developers use different recommended technologies together, so that the current hybrid recommendation method is slowly formed.

In today's e-commerce field, the use of collaborative filtering recommendation algorithms is particularly wide. This method first finds out the target user's preferences similar to other users, and then pushes these similar user favorite projects to the corresponding target users. The logic behind it is actually simple, that is, users with similar tastes are more likely to be interested in the same type of

ISSN 2616-5902 Vol. 8, Issue 9: 99-110, DOI: 10.25236/AJBM.2026.080912

items. The most commonly used collaborative filtering algorithms can now be divided into two types, namely, item-based methods and user-based methods. Collaborative filtering is a recommendation technology that is now used a lot, which organizes and analyzes the interaction data between users and items, finds similar user groups, and then refers to the preferences of these similar users to push the appropriate item to the target user [11].

In addition, there is also a content-based filtering that collates the properties of the item itself, then matches the user's personal preference portrait, and pushes the user to the content that is more similar to the item they have previously liked [10]. The hybrid recommendation systems combine the advantages of collaborative filtering and content-based filtering to significantly improve the accuracy of recommendations and make the coverage of the content wider [4].

Specifically, the operation logic of personalized recommendation algorithms can be divided into four different parts, and Tmall is taken as a well known example.

Firstly, if the user has previously consumed the store and it matches the user's current search demand, the system gives priority to launching this kind of "once purchased shop". These stores are placed in a more prominent position to make it easier for users to see. The system also prioritizes the top spot for the user who has previously liked or visited the store.

Secondly, the system collects various types of behavior data of users to analyze, and finally generates corresponding recommended content. The user's browsing history, searched-for keywords, favorite goods, and items added to the shopping cart are recorded as reference the for personalized recommendation. After the user searches or browses a certain category of goods, the next time the user opens Tmall, such products appear in the "recommended for you" section.

Thirdly, the personalized recommendation systems match the user's previous consumer behavior data with user's personalized labels. These labels contain information such age, gender, interests and constellations, after which a big related data analysis is conducted to priority the stores or products with high matching degree for these labels to correspond consumers;

Fourthly, the system relies on probability matching to give recommendations. If there is no record of the consumption behavior of a user, this situation mostly appears for the newly registered users, For instance, if the new user wants to buy a dress, this kind of dress has several different styles including Chinese, Korean, European and American styles. The system analyzes the data of consumers who have searched for the "dress" before, and can find that more than about 80% of consumers finally bought Chinese style dresses, so the system gives priority to showing this higher probability style and to the new buyers.

2.3. Empirical Studies

Findings from the prior empirical studies reveals that personalized product recommendations have a practical role in optimizing the actual user experience and driving the growth of platform sales. Adomavicius and Tuzhilin(2025) counted the operating data of multiple online bookstores and found that using the appropriate personalized recommendation strategy can significantly improve the user's click-through rate of goods[1], and also make users more likely to finally place an order. Similarly, Lee & Hosanagar (2021) collated and analyzed the actual operation data of multiple domestic e-commerce platforms and found that the personalized recommendation scheme generated by collaborative filtering algorithms has actually performed much better than ordinary non-personalized recommendations in terms of improving user engagement and improving user conversion rates[8].

Kumar & Hosanagar (2019) examined the practical impact of personalized product recommendations on consumer purchase outcomes in the online retail environment[7]. The results show that there is a strong positive correlation between personalized recommendations and consumer purchase intentions, demonstrating that recommendation systems do have a great impact on consumer behavior. In line with their research, Sharma et al. (2025) demonstrated that consumer trust in recommendation algorithms and perceived personalization are key drivers of online purchase intention within e-commerce contexts[9]. Excessive or poorly-targeted personalized recommendations may trigger consumers' privacy concerns and offset part of the conversion-boosting value delivered by recommendation systems. Accordingly, the practical effectiveness of personalized-recommendation algorithms depends not only on technical accuracy, but also on consumers' psychological interpretation and acceptance of the tailored outputs generated by such algorithms.

To sum up, the existing studies provide valuable insights to prove that the overall use of

ISSN 2616-5902 Vol. 8, Issue 9: 99-110, DOI: 10.25236/AJBM.2026.080912

personalized suggestions is useful, but these studies basically do not involve the specific role of these suggestions on the actual purchase behavior of Chinese online shoppers. It is necessary to disassemble the actual role of personalized recommendations in greater detail and carry out corresponding research. In the current relevant research, few scholars pay attention to the demographic variables of age, gender and income, what kind of moderating effect these variables exert on domestic consumers' purchasing decisions when they face personalized recommendations. Therefore, the purpose of this study is to comprehensively understand the specific impact of personalized product recommendations on the purchase behavior, and address the gaps in the relevant research.

3. Research Methodology

3.1. Research Design

The method of research used in this study is survey research. A survey is a good way to study how personalized product recommendations influence the purchasing decisions of online shoppers as it can collect numerical data from a large and diverse group of participants. The present technique helps the researchers to gain the knowledge of the respondents' perception, attitude and behavior concerning personalized product recommendations and online shopping as per the objectives of the study.

3.2. Participants

In this paper, 106 Chinese online buyers were the subjects. The characteristics of the sample are demographics, such as age, gender, monthly income, and highest level of education attained . The sampling technique used in this study involved both probability and non-probability sampling methods to get a representative sample of the target population.

3.3. Data Collection

The data was collected by an online questionnaire distributed to the target population on the Wenjuanxing platform. The questionnaire comprises of multiple choice and Likert scale questions relating to different aspects of online shopping habits, perceptions of personalized product recommendations, purchasing behavior and demographic factors. Data was kept anonymous and confidential and informed consent was obtained to ensure the validity and the reliability of data.

3.4. Data Analysis

Quantitative data analysis techniques were used to analyze the collected data. Descriptive statistics was used to provide an overview of the responses of the participants including frequencies, percentages, mean and standard deviations. Hypotheses were tested using inferential statistical analyzes, including correlation and regression analyzes to examine relationships among variables. Statistical software was used to assist the data analysis, which ensured rigor and accuracy in the results.

3.5. Ethical Consideration

The survey was highly confidential and it was not possible to mention specific names in the report. The technique of voluntary investigation was applied to protect the rights of the respondents. The privacy of the data collected and the information obtained during this period was of the highest confidence.

4. Results and discussion

Table 1: Percentage Distribution of the Respondents' Profile

Demographic Variable	Frequency	Percentage (%)
Gender		
Male	44	41.5
Female	62	58.5
Age		
19-30years old	41	38.7

ISSN 2616-5902 Vol. 8, Issue 9: 99-110, DOI: 10.25236/AJBM.2026.080912

31-40 years old	27	25.5
41-50 years old	25	23.6
51years old and above	13	12.3
High Education Level		
High School and Below	19	17.9
Bechelor's Degree	77	72.6
Master's Degree	8	7.5
Ph.D. or Above	2	1.9
Income		
2000RMB and Below	18	17.0
2000-5000RMB	32	30.2
5000-8000RMB	26	24.5
8000-10000RMB	13	12.3
10000RMB and Above	17	16.0

The results show the percentage distribution of the profile of the respondents. The table shows the gender, age, level of higher education and income of the respondents. It shows that from the 106 respondents, there are 62 female respondents and 44 male respondents which account for 58.5% and 41.5%, respectively. Clearly, female respondents are more than male respondents.

According to the age distribution data, respondents aged 19-30 constitute the largest group, accounting for 38.7%. The second-highest age group is the 31-40, representing 25.5%. The proportion of the 41-50 age group and the age group aged 51 and over are 23.6% and 12.3%, respectively. From the overall data, the respondents are distributed across age ranges, and most of the respondents are within the age range of young people to middle-aged group.

Concerning the highest education level, the majority of respondents have a bachelor degree, 72.6%. 17.9% have a high school education or lower, while 7.5% have a master's degree. Only 1.9% of respondents reported having a Ph.D. or higher. The data suggests a majority of respondents have at least a bachelor's degree, indicating a relatively educated sample population.

The largest income bracket among respondents is 2000-5000 RMB, which accounts for 30.2% of the sample. The next most common income range is 5000-8000 RMB, at 24.5% of the respondents. The percentages of income levels 8000-10000 RMB and 10000 RMB and above are close, at 12.3% and 16.0% respectively.17.0% of the respondents are in the lowest income bracket (2000 RMB and below). The monthly income levels are distributed with a variation among the respondents. A good number of respondents are in the middle income level.

Overall, Table1 reveals that respondents of different genders, different ages, different education levels and different income levels have corresponding distributions in the sample, and this information enables a clear understanding of the basic characteristics of the entire sample population. These collated information can be used as a basis for further research to explore these demographic features, specifically their relationships with respondents' views on personalized product recommendations, and their actual online purchase behavior.

Table 2: Online Shopping Habits

	Online Shopping Frequency	Online Shopping Satisfaction	Likelihood of Recommending Online Shopping
N	106	106	106
Missing	0	0	0
Mean	2.54	2.20	2.27
Median	3.00	2.00	2.00
Standard deviation	0.620	0.506	0.640
Minimum	1	1	1
Maximum	3	3	3

Table 2 specifically presents current consumers' online shopping habits. These data obtained from the actual survey can offer a clearer understanding of the online shopping habits of the surveyed individuals, and they can also intuitively show the frequency of different respondents' participation in online shopping, their satisfaction with all aspects of online shopping, and their willingness to recommend the commonly used online shopping platform or channel to others.

ISSN 2616-5902 Vol. 8, Issue 9: 99-110, DOI: 10.25236/AJBM.2026.080912

In general, the respondents have the habit of shopping on the Internet platform on average, and the average score of this item is 2.54, and the median specific value of the statistical online shopping frequency is 3.00. The result indicates that a high proportion of the sample respondents are actively involved in different online shopping activities. The relatively high mean score indicates that respondents frequently engage in online shopping. Although the frequency of online shopping is not low, the compiled data can also reflect that the satisfaction of respondents in their online shopping experience is in the range of relatively neutral, the average score of this item is calculated to be 2.20, the median specific value is 2.00. The result can indicate that respondents' satisfaction with the overall shopping experience is not biased to a particularly positive evaluation or negative evaluation, and their view is relatively balanced.

Additionally, respondents have a neutral position on the possibility of recommending online shopping to friends or family, with an average score of 2.27 and a median of 2.00. They are relatively neutral in their attitude toward recommending this way of shopping to others. This also shows that although online shopping may have been a common practice, their overall satisfaction and the tendency to actively advocate online shopping to others are not overwhelmingly positive [1]. As a result, it is vital to better understand what factors influence user satisfaction and active recommendation willingness within the online-shopping domain, which can support adjustment and optimization of relevant strategies for improving user experience and help foster positive recommendations.

Table 3: Personalized Product Recommendations

	Frequency of Personalized Product Recommendations	Perception of Personalized Product Recommendations	Influence of Personalized product Recommendations on Purchasing Decisions	Likelihood of Exploring Personally Recommended Products	Perceived Enhancement of Shopping Experience by Personalized Product Recommendations
N	106	106	106	106	106
Missing	0	0	0	0	0
Mean	2.22	1.95	2.00	2.02	1.97
Median	2.00	2.00	2.00	2.00	2.00
Standard deviation	0.704	0.523	0.586	0.569	0.683
Minimum	1	1	1	1	1
Maximum	3	3	3	3	3

Table 3 indicates that personalized product recommendations are very common for these people interviewed. The average frequency score of personalized product recommendations is 2.22, and the median is 2.00. This statistical result is in line with the current development trend in the field of e-commerce, and now all platforms are optimizing the user's shopping experience in a personalized recommendation way, and also want to drive the platform's product sales in this way. However, it can also be seen that although users encounter such recommendations with high frequency, the overall attitude to these recommendations is neutral, with an average score of 1.95 and a median of 2.00. This also shows that even if almost every shopping platform adopts personalized recommendation, users generally hold a neutral perception of these recommendations, which reveals the current recommendation algorithm and operation strategy have many areas that can be adjusted and optimized [13].

In addition, the data illustrates what role personalized product recommendations play in purchasing behavior, yielding many previously overlooked detailed conclusions. Respondents received various personalized recommendations when they usually shop online, but they felt that the impact of these recommendations on their final purchase of things was not large, and the attitude was biased towards neutrality, the average of relevant scores was 2.00, and the median was 2.00. This result shows that personalized recommendations may indeed have some impact on the user's purchase behavior, but this effect cannot play a great role for all users, let alone directly determine the user's purchase choice [10]. Respondents also stated that they were also at a moderate level of willingness to explore recommended products, with an average score of 2.02 and a median of 2.00. User's attitude towards the recommended products can also show that the relationship between personalized recommendations and actual consumer behavior is actually very complicated, and further research is required to identify what factors will affect the user's willingness to engage with recommended content[4].

Furthermore, this can be observed whether respondents perceive that personalized product

ISSN 2616-5902 Vol. 8, Issue 9: 99-110, DOI: 10.25236/AJBM.2026.080912

recommendations can improve their shopping experience, with an overall neutral attitude, a mean score of 1.97, and a median of 2.00. When the platform is designed to personalize the recommendation function, the original idea is to help users simplify the selection process when shopping, and better fit each user's own preferences. However, based on the actual feedback from the respondents, there remains much room for adjustment and optimization for recommendation content. These findings indicate that attention should be paid to the optimization of the recommendation algorithm and the related push strategy, so that the pushed content is more appropriate to the user's usual preferences and actual shopping needs, and overall online shopping experience can be improved. The standard-deviation statistic suggests that different users differ in the acceptance of such recommendations and habits. Further designs for personalized recommendations on online platforms should also take into account the differences among various users and adopt more targeted push programs.

Table4: Purchasing Behavior

	Average Monthly Online Spending	Frequency of Purchases Based on Personalized Product Recommendations	Satisfaction with Products Purchased Based on Personalized Recommendations
N	106	106	106
Missing	0	0	0
Mean	1.95	1.92	1.96
Median	2.00	2.00	2.00
Standard deviation	0.638	0.619	0.412
Minimum	1	1	1
Maximum	3	3	3

Table 4 compiled presents the information on respondents' various types of purchasing behavior in the online shopping scene. These habits are reflected in their daily consumption habits, the frequency of personalized related purchases, and the satisfaction of the purchased goods. First of all, moderate spending patterns on online purchases, with a mean score of 1.95 and a median of 2.00 for the amount spent per transaction. This result is in line with the current overall development trend in the field of e-commerce, where consumers often make varying levels of financial commitment per transaction, influenced by factors such as product value and perceived utility [3]. From another part of the data, it can also be seen that respondents make purchases based on the personalized recommendations, with a mean score of 1.92 and a median of 2.00. This result can also reveal that the personalized recommendations given by the platform indeed affects consumers' shopping choices, and they can also play an important role in users' decisions to eventually buy a certain product.

Besides, the respondents were at a medium level of satisfaction with the products they purchased online, with a mean score of 1.96 and a median of 2.00. This result illustrates that even if the respondents usually are habituated to online shopping, they often receive personalized recommendations from the platform, and their overall satisfaction with the products they buy is still neutral. This finding highlights that the e-commerce industry now really needs to improve the quality of the product itself on the basis of the existing one, as well as the service experience of the delivery process, so that consumers can be more satisfied and more willing to choose the same platform for a long time [5]. In addition, the standard deviation values indicate some variation in respondents' responses. Hence, follow-up research should continue to find out the factors that affect everyone's online shopping satisfaction, as well as the usual consumption expenditure habits. They can be used to adjust the relevant operating strategies of digital retail, bringing consumers a better shopping experience and loyalty.

ISSN 2616-5902 Vol. 8, Issue 9: 99-110, DOI: 10.25236/AJBM.2026.080912

Table 5: Demographic Factors

	Importance of Age in Response to Personalized Product Recommendations	Importance of Gender in Response to Personalized Product Recommendations	Importance of Monthly Income in Response to Personalized Product Recommendations
N	106	106	106
Missing	0	0	0
Mean	1.92	1.83	2.09
Median	2.00	2.00	2.00
Standard deviation	0.587	0.654	0.724
Minimum	1	1	1
Maximum	3	3	3

Table 5 intuitively reflects how the respondents view the impact of demographic factors on their online purchasing behavior, including age, gender and monthly income. Respondents generally felt that their age was moderately influential in online shopping decisions, with a mean score of 1.92 and a median of 2.00. The result suggests that age may affect consumer behavior in the digital marketplace, but it's influence is not overwhelmingly strong. Respondents also mentioned that their gender has a smaller effect on online purchases, with a mean score of 1.83, corresponding to a median of 2.00. This finding shows that the influence of gender in consumer decision-making is actually nuanced, factors such as everyone's usual product preferences, daily development of shopping habits may exert different degree of influence on consumer behavior [12].

In addition, respondents generally believed that their monthly income was relatively more important in various factors that affected their online purchase behavior, with a mean score of 2.09 and a median of 2.00. This result shows that the income level play a great role in consumer-behavior choices with the digital consumption scenario. When the disposable income is higher, individuals naturally have stronger purchasing power, which may slowly change individuals' usual consumption expenditure habits. After counting the standard deviation of each demographic-related factor, it can be seen that there are some differences in the views of different respondents on these factors. As such, the deep logic behind these relationships among multiple factors should be explored further, and the relevant conclusions can also be used to develop targeted marketing strategies for the e-commerce industry, as well as to build a valuable personalized recommendation system.

Table 6: Relationship between Personalized Product Recommendations and Purchasing Behavior

		Personalized Product Recommendations	Purchasing Behavior
Personalized Product Recommendations	Pearson's r	—	
	df	—	
	p-value	—	
	N	—	
Purchasing Behavior	Pearson's r	0.656***	—
	df	104	—
	p-value	< .001	—
	N	106	—

Note. * p < .05, ** p < .01, *** p < .001

Table 6 presents the relationship between personalized product recommendations and consumer purchasing behavior. The data clearly reflects the positive correlation between personalized product recommendations and purchase behavior, with a p-value result less than 0.001. Higher levels of personalized product recommendations are associated with higher levels of purchasing behavior among the respondents. The results are consistent with Alomari et al. (2022) study, which revealed that personalized recommendations do have a good effect on promoting consumers to make purchasing decisions[2]. This strong positive correlation can also show that consumers generally give a more

ISSN 2616-5902 Vol. 8, Issue 9: 99-110, DOI: 10.25236/AJBM.2026.080912

positive response to the personalized product recommendations generated by the platform according to their own consumption preferences and usual browsing history, which is associated with a greater likelihood of making purchases.

Additionally, the robust correlation between personalized product recommendations and consumer purchasing behavior, with a coefficient of 0.656, highlights that the personalized recommendation system is important for improving the overall operation performance of the e-commerce platform. This finding can also reflect that the e-commerce platform uses more mature algorithms, corresponding data-analytics technologies to generate the personalized recommendation content matching consumers' actual preferences, and such content carries great practical value. In this way, these optimization measures can improve consumers' purchase intentions and help the platform to increase the overall conversion rate.

Model Fit Measures

Model	R	R^2
1	0.656	0.430

Model Coefficients - Purchasing Behavior

Predictor	Estimate	SE	t	p
Intercept	3.117	0.5425	5.75	< .001
Personalized Product Recommendations	0.462	0.0522	8.86	< .001

Figure 1: Regression Analysis Between Personalized Product Recommendations and Purchasing Behavior

Figure 1 lists the specific results of linear regression analysis, which mainly studies the relationship between personalized product recommendations and user purchase behavior. The calculated model shows that the regression model is statistically significant, and the corresponding R2 value is calculated as 0.430. This value reveals that there are approximately 43% of the variance in purchasing behavior can be reasonably explained by the changes in personalized product recommendations.

Moving to the model coefficients, regression analysis estimates what kind of impact personalized product recommendations have on user purchase behavior. The coefficient estimate of the personalized product recommendation represents the expected change in the dependent variable corresponding to the purchase behavior when the independent variable is increased by one unit of the personalized product recommendation. The positive coefficient means that the value recommended by the personalized product rises, and the value of the purchase behavior also rises accordingly; in contrast, the negative coefficient means that the change direction of the two is the opposite [6].

Analyzing the coefficients in the model, the intercept term, which represents the value of the personalized product recommendation is zero. The expected value of the purchase behavior is estimated at 3.117 with a standard error of 0.5425. The coefficient for personalized product recommendations is statistically significant ($p < .001$), with an estimate of 0.462 and a standard error of 0.0522. It can be seen that under the premise that all other influencing factors remain unchanged, for each additional unit of personalized product recommendations, the purchase behavior increases by about 0.462 units correspondingly. The t value of 8.86 further supports this coefficient, indicating that there is a significant positive relationship between personalized recommendations and purchase behavior. Therefore, these findings demonstrate the importance of tailored product suggestions in influencing consumer decisions and driving engagement on online shopping platforms.

Model Fit Measures

				Overall Model Test			
Model	R	R^2	Adjusted R^2	F	df1	df2	p
1	0.726	0.527	0.466	8.63	12	93	< .001

Figure 2: Model Fit Measures

ISSN 2616-5902 Vol. 8, Issue 9: 99-110, DOI: 10.25236/AJBM.2026.080912

Table 7: Multiple Regression Analysis of Demographic Factors and Personalized Product Recommendations on Purchasing Behavior

Predictor	**Estimate**	**SE**	**t**	**p**
Intercept [a]	2.8815	0.6383	4.5144	< .001
Personalized Product Recommendations	0.4337	0.0540	8.0357	< .001
Gender:				
female – male	0.9111	0.2872	3.1721	0.002
Age:				
31-40years old – 19-30years old	-0.2988	0.3344	-0.8935	0.374
41-50years old – 19-30years old	-0.2946	0.3427	-0.8596	0.392
51years old and above – 19-30years old	-0.3789	0.5546	-0.6832	0.496
Highest Education Level:				
Bechelor's Degree – High School and Below	-0.2215	0.3401	-0.6513	0.516
Master's Degree – High School and Below	-0.6040	0.6967	-0.8670	0.388
Ph.D. and Above – High School and Below	-0.8753	0.9808	-0.8925	0.374
Monthly Income:				
2000-5000RMB – 2000RMB and Below	0.0317	0.3465	0.0914	0.927
5000-8000RMB – 2000RMB and Below	1.0608	0.3968	2.6734	0.009
8000-10000RMB – 2000RMB and Below	0.3127	0.5773	0.5417	0.589
10000RMB and Above – 2000RMB and Below	0.6092	0.5271	1.1557	0.251

The full results of the linear regression analysis are reported in Figure 2 and Table 7, mainly to investigate the specific relationship between personalized product recommendations and user purchase behavior. The effects of several demographic factors such as gender, age, education level and monthly income have also been incorporated into the scope of consideration in the analysis process. The model fit measures indicate that this regression model explains a large part of the variance in the purchase behavior and the final R-squared value is 0.527, which indicates that almost 52.7% of the variability in the purchase behavior can be explained by the various predictors included in the model. The results of the overall model test carried out by us are statistically significant ($p < 0.001$), which also shows a good adaptation of the overall regression model to the existing data.

Moreover, findings reveal that the variable of gender has a significant effect on purchasing behavior, and with males used as a reference group, the female group is more likely to show purchasing behavior, with the corresponding estimate of 0.9111 and p-value equal to 0.002. Other demographic factors, such as the user's age, education level, do not show significant effects on the purchase behavior, while one monthly income category (5000-8000RMB) shows a significant difference compared with the reference group (2000RMB and below, p=0.009).

Table 8: Percentage Distribution of Influential Personalized Product Recommendation Types

Personalized Product Recommendation Type	Frequency	Percentage (%)	
Recommended for You	33	31.9	
Frequently Bought Together	37	34.9	
Recently Viewed	43	40.6	
Similar Products	32	30.2	
Recommended by Influencers	39	36.8	

Table 8 reports the percentage distribution of influential personalized product recommendation types among Chinese online buyers.

"Recently viewed" suggestions ranked at the top, accounting for 40.6%, which can also show that the recommendations generated by reference to user browsing history have a great impact on consumers' final purchase decisions. Ranking second is the "frequently Bought Together" recommendation, constituting 34.9%, which indicates that the social proof and product bundling of such strategies indeed play a good role in affecting consumers' final selection. "Recommendation by Influencers" and "Recommended for You" these two kinds of recommendations also have a great impact, and the influence of "Similar Products" is relatively small, representing 30.2%, showing that compared with other recommended forms, the driving effect of product similarity on consumer choice is weaker.

These results underscore the practical value of personalized recommendation strategies in the field

ISSN 2616-5902 Vol. 8, Issue 9: 99-110, DOI: 10.25236/AJBM.2026.080912

of e-commerce. After enterprises understand what type of recommendation consumers prefer, they can adjust their algorithms and marketing-related arrangements to further enhance users' engagement and final sales. Therefore, these findings can also provide direction for the design of the recommendation system, which is more tailored to the actual preferences of consumers, and can bring users a more comfortable and personalized online shopping experience.

5. Conclusion

A relatively complete analysis was performed to identify what kind of impact personalized product recommendations exert on domestic online buyers' purchase decisions. The results of the study show that personalized recommendations play a great role in shaping consumer behavior in the digital market. A more detailed examination reveals a positive relationship between personalized recommendations provided to online buyers and their purching behavior. It also reflects that customized product recommendations based on users' needs can play a vital role in driving product sales and enhancing the overall shopping experience of consumers.

Moreover, the study also examines the complex interplay between demographic factors and the practical role of personalized recommendations. After analyzing demographic characteristics such as age, gender, education level, and income, useful conclusions are drawn about the effects of these factors and personalized recommendation on purchase behavior. The analysis provides a better understanding of the significant association between gender and purchase behavior. The results show that when designing and implementing personalized recommendation-related strategies, small differences in population characteristics should be taken into account, so as to enhance the practical role of recommendations as much as possible, and render the recommended content more compatible with the needs of different consumer groups in the Chinese market.

Furthermore, the study identifies the types of personalized product recommendations that have the most prominent effects on online buyer purchase behavior. By conducting a detailed analysis of the collected data, the study finally determined that the common types of recommendations such as "Recently Viewed" and "Frequently Bought Together" play important roles in the whole process of consumers making purchasing decisions. These collated conclusions can provide practical direction for e-commerce companies that need to optimize the recommendation algorithm, and adjust their existing marketing strategies based on these conclusions to better adapt to the shopping preferences and online browsing habits of Chinese consumers.

In conclusion, the research completed has sorted out the relationship between personalized recommendations and user purchase behavior in the Chinese e-commerce market. Companies can refer to the findings of this study to adjust their marketing plans, better foster customers engagement, and achieve sustainable growth within rapidly evolving online retail environment.

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