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# *How Do Personalized Recommendations Influence Purchasing Intent?*

**Xiangtian Ji[1*], Mingyu Zhang[2], Shuxin Shan[3], Enge Zhang[4]**

*[1]Business School, University of Birmingham, Birmingham, UK*
*[2]St Margaret's Anglican Girls School, Brisbane, Australia*
*[3]Macau University of Science and Technology, Macau, China*
*[4]DaoXiangHu International School, Beijing, China*
**Corresponding Author. Email: xxj323@student.bham.ac.uk*

***Abstract:*** Personalized Recommendation Systems (PRS) is becoming an important tool to improve consumers' engagement and satification in digital commerce area. This study explores the impact of PRS on purchase intention, analyzing how factors such as trust, perceived relevance, frequencies, usage level, consumption clarity. With the use of quantitative method, the data was collected by using surveys and analyzed by the use of SPSS to find the relationship between PRS and consumers' purchase intention. This finding indicates that PRS with high accuracy can significantly enhance consumers' confidence and reduce the fatigue from PRS. However, the excessive and over-repeated recommendations may give consumers a feeling of be monitored and lead to privacy concern, fatigue and affecting consumer trust. This research is contributed to the growing industry of e-commerce and give out unique viewpoint of using PRS to improve consumer experience and sales performance.

***Keywords:*** Personalized Recommendation Systems, Purchase Intention, Filter Bubbles, E-commerce, TaoBao.

## 1. Introduction

Personalized Recommendation Systems (PRS) have become essential for today's e-commerce platforms, transforming how shoppers find, assess, and buy products. These systems tap into user data, including browsing history, search habits, and previous purchases, to offer customized product suggestions. The goal is simple: enhance user experience, boost engagement, and increase sales. On platforms like Taobao, PRS are always on, delivering real-time recommendations based on both direct feedback and subtle signals from users. As these systems advance, so too does the complexity of how consumers behave. It's important to note that the success of PRS isn't just about how accurate the predictions are; it's also about how shoppers perceive and react to them in different situations. Factors like how often recommendations appear and how clear users are about their shopping intentions significantly influence buying decisions. When implemented effectively, PRS can aid in decision-making and boost customer satisfaction. However, there are still unanswered questions about how repeated exposure to recommendations affects trust, engagement, and purchasing actions.

This study delves into the link between the use of PRS and consumer purchase intentions, guided by three key hypotheses: (1) the connection between increasing recommendation frequency and

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purchase intention resembles an inverted U-shape; (2) consumers with well-defined shopping goals are more inclined to make purchases based on recommendations; and (3) frequent use of PRS may lead to lower purchase intentions. To explore these ideas, a quantitative research design was employed, featuring an online questionnaire distributed through snowball sampling and analyzed with SPSS tools, including linear regression and Pearson correlation.

Beginning with a review of relevant literature, this paper examines the design, advantages, risks, and behavioral effects of personalized recommendation systems. It then outlines the research methodology, covering data collection, analysis techniques, and ethical considerations. Finally, the findings are presented, followed by a discussion on their implications. Together, these elements offer a thorough analysis of the effectiveness of PRS within Taobao's e-commerce landscape.

## 2. Literature review

### 2.1. Personalized recommendation systems

By analyzing users' prior actions, preferences, and contextual data, tailored recommendation content is supplied to users through Personalized Recommendation Systems. This helps them locate products, services, or information of interest from extensive databases, thereby enhancing their satisfaction and engagement while reducing their information search effort [1]. The explosion of information has made personalized recommendation systems ubiquitous across industries such as e-commerce, music, video streaming, and news outlets.

In e-commerce websites like Taobao, personalized recommendation systems offer customized product suggestions based on retrieved and analyzed browsing and purchase history, as well as searching activity including keywords. These systems employ a more sophisticated approach than solely relying on explicit feedback in the form of ratings and reviews. These systems are also able to infer what users like based on implicit feedback received through browsing history and the duration of their visit [2]. In this manner, personalized recommendation greatly increases click rates, purchase conversion rates, and overall user engagement for the platform [3].

As a rule, tailored recommendation systems increase the accuracy of meeting user expectations, enhancing user participation and purchase intention. However, too much focus on the user’s previous data might make the content monotonous, which in turn makes the system less dynamic and appealing. Hence, continuous optimization of the recommendation algorithm is essential.

### 2.2. Advantages of personalized recommendation systems

E-commerce platforms can offer personalized product suggestions that closely align with individual needs that ultimately enhancing the shopping experience of consumers' by analyzing browsing habits, purchase history, and past preferences [3]. These recommendations are especially helpful when shoppers don't have a clear goal in mind. Since, recommendations then can introduce users to new product categories or solutions they might not have discovered otherwise [4].

Click-through rate and data also play a key role in improving personalized recommendations. The more specific and relevant the suggestions are, the more likely users are to engage with the app from: clicking, exploring, and potentially making a purchase [4].

Consumers are more likely to trust and accept AI-driven tools when they see that the recommendations are accurate and genuinely helpful. When the system can anticipate their needs based on past behavior, it reinforces the idea that the technology adds value [4].

Personalized recommendations help meet the diverse needs of shoppers by factoring in a range of user behaviors and preferences. This allows platforms to present a broader variety of relevant products tailored to different consumer profiles [4].

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### 2.3. Filter bubbles in personalized recommendations

Although developed to improve personalization, recommender systems may negatively affect consumer purchase intent by filtering out too many options [5]. This is known as “filter bubble” that breed stagnation and occurs when users get consistent results that only match their past choices instead of being offered a wide range of products or ideas [5]. The broader problem is that, over time, this monotony, coupled with the perception of limited options, will result in disengagement or “user fatigue” [5]. This is the problem that Taobao or other Chinese e-commerce platforms face; if their algorithms are overly tailored, users will never be able to discover new or different products. Such an algorithmic approach where novelty and variety becomes extinct reduces the probability of making purchases [5].

Filter bubbles restrict the chances for customers to find alternate products which could fulfill their needs thus stalling their decision-making progression [5]. The continuous feedback cycle creates restriction in product discovery while simultaneously damaging user trust and interest [5]. The reduction of filter bubbles demands algorithms to include diversity while adding novelty aspects as well as promote serendipitous moments in recommendations [5]. The combination of personalized unexpected recommender systems and cross-domain models achieves the goal of accuracy while expanding user exposure to encourage purchase decisions [5]. Platfoms can enhance consumer satisfaction through a diverse experience by breaking the pattern of duplicate recommendations which leads to higher purchase intent [5].

### 2.4. Overuse of personalized recommendations

Contemporary digital commerce increasingly deploys algorithmic recommendation architectures [6] as strategic tools for experience personalization and revenue maximization. While initial implementation phases demonstrate measurable performance improvements [7], critical scholarship identifies counterproductive outcomes emerging from sustained system operation [8-9].

Technical analyses reveal that collaborative filtering architecture systematically amplifies market concentration effects. Through iterative exposure cycles, users become progressively confined within algorithmically constructed consumption corridors [10]. Such distribution dynamics not only suppress long-tail product visibility but also induce measurable cognitive strain, with longitudinal studies documenting increase in decision abandonment rates under high-frequency recommendation conditions [11]. The behavioral economics perspective further illuminates this paradox. User preference formation demonstrates marked path dependency under algorithmic guidance systems [12]. Experimental cohorts exposed to standardized recommendation protocols exhibited reduction in exploratory purchasing behavior compared to control groups [7]. This behavioral convergence effect fundamentally alters marketplace dynamics, creating self-perpetuating cycles where algorithmic predictions progressively shape the consumption patterns they purport to reflect [8]. Emerging mitigation frameworks emphasize the necessity of introducing stochastic elements into recommendation algorithms. Hybrid architecture combining collaborative filtering with serendipity engineering [6] demonstrate potential to reduce popularity bias by 22-38% while maintaining conversion rates [9]. These adaptive systems exemplify the required balance between predictive accuracy and exploratory design space preservation.

### 2.5. Personalized recommendation systems and individuals ’purchase intention

The Personalized Recommendation Systems (PRS) find widespread use in online shopping platform to enhance consumer purchase intention. Behera et al. found that the consumers' purchase behavior will increase by 1.93% through the influence of PRS. PRS can meet consumers' needs more and thus increase consumer purchase intention [13]. Behera et al. mentioned that PRS also help to increase

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average order value by 32.79% which because PRS can recommend product that are more fit with consumers' need. Researchers also find that PRS has improved the convenience of mobile shopping and influence consumers positive and negative emotions which also affect consumers purchase intention [14].

In conclusion, personalised recommendation systems play an important role in improving consumers' purchase intention and shopping experience through many aspects in online shopping platforms. PRS provides appropriate product and better shopping experience to increase purchase intention and average order value. However, customer purchase intention could also be influenced by recommendation frequencies and their purchase clarity which remains an gap on research. Thus, the following two hypothesis is proposed accordingly:

*H1: The relationship between increasing frequency of AI-based Personalized Recommendation purchasing intention is inverse U-shaped*

*H2: People with clear consumption goal are more likely to make a purchase decision recommended by Recommendation Systems*

*H3: Higher frequency of Personalised Recommendation System usage leads to a decrease in consumers' purchase intentions*

## 3. Methodology

### 3.1. Introduction

This study used a quantitative approach to explore how AI recommendation systems on Taobao affect consumer purchase intentions. Data was collected via an online questionnaire using snowball sampling, with a focus on the relations between purchase intention to recommendation frequency, and shopping goal clarity. The research design covered sampling, data collection, and analysis methods. Ethical considerations were addressed through informed consent and data confidentiality. This methodology aimed to provide reliable insights into Taobao users' responses to personalized recommendations.

### 3.2. Research design

The impersonal survey design was chosen to collect data in this research as the use of Personalized recommendation systems is acted in every second. The questionnaire is appropriate for gathering data from participants in any time and this design was chosen because it can make an efficient data collection. The survey design are suitable for capture information about peoples' attitude to personalized recommendation systems.

This research used the quantitative method enable to find how people likely to purchase in the influence of Personalized recommendation systems, as the quantitative method can use the statistical method for analysis to identify the relationships. The quantitative data are collected using structured questionnaire distributed to respondents via online platforms. The online questionnaire was chosen because of the efficiency, cost-effectiveness, and it can be through a high number to populations. It is designed to be concise and user-friendly to improve the response rate. This questionnaire consisted 14 multiple choices question including demographic information, Frequencies & the purchase intention, and the consumption goal clarity & purchase intention

### 3.3. Sampling (population, sampling method)

This research targets people who use TaoBao as a shopping platform with no limitation on age and gender. This ensures that all data from individuals filling in the questionnaire would be relevant on data about personalized recommendations.

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In this study, we employed Snowball sampling as the recruitment method. This involves participants who complete the questionnaire being asked to help identify other potential individuals for the study. This process continues until the desired sample size is achieved or until no new referrals are generated from the respondents' data. Snowball sampling offers several advantages, including being time-efficient, easy for respondents to participate in, and cost-effective. However, it also has limitations, such as potential bias due to participants referring to people they know, which can lead to unequal representation in the sample group. Given the constraints of time and resources, we opted for Snowball sampling. We estimated a sample size of 200 responses for this research.

### 3.4. Data analysis

In this research, we used SPSS to help us do data analysis. We used numbers 1–5 to represent different degrees of possibility, respectively: very possible, possible, general, impossible, and very impossible. For example, the linear regression analysis result and the frequency analysis results have helped us to prove our first hypothesis. Through these precise data analyses, we can better understand the results of data processing. Besides, through the F-test analysis results on how shopping goal clarity (yes or no) affects the purchase decision recommended by recommender systems, we found that the second hypothesis is clearly true. And we used Pearson correlation and linear regression analysis results to support the third hypothesis.

### 3.5. Ethical consideration

Ethical considerations were carefully addressed in this research to protect participants' rights and ensure data integrity. On the first page of the questionnaire, participants were provided with clear information regarding the purpose of the study, the handling of their personal data, and their rights as respondents. They were required to give informed consent before proceeding. Participation in the study was entirely voluntary, and respondents were free to withdraw at any time without providing a reason. All personal data collected was handled confidentially, and no personally identifiable information was disclosed.

This methology provides a framework for exploring the results of personalized recommendation on purchasing intent on TaoBao. By using an impersonal survey design, snowball sampling, and data analysis. This research aims to contribute to the aplication and academic knowledge. The Ethics and limitations were considered carefully to enhance the research’s integrity and validity.

## 4. Findings

### 4.1. Demographic information

The first part of the questionnaire results provided a detailed demographic and behavioural insight into the respondents. Regarding gender distribution, 53.8% (99 respondents) are female, while 46.2% (85 respondents) are male. Age-wise, the most represented group is 18-25 years old (40 respondents, 21.7%), followed by above 50 years old (30 respondents, 16.3%), and 31-35 years old (22 respondents, 12%). The 26-30 age group consists of 20 respondents (10.9%), while the 46-50 group includes 21 respondents (11.4%). The 41-45 group comprises 17 respondents (9.2%), and the 36-40 age group accounts for 15 respondents (8.2%). The youngest category, under 18, makes up 19 respondents (10.3%). Regarding monthly income, the highest proportion of respondents, 54 people (29.3%), earn between 3,000 and 8,000 yuan per month, while 39 respondents (21.2%) fall into the 8,000–10,000 yuan range. Additionally, 33 respondents (17.9%) earn between 0 and 3,000 yuan, while 30 (16.3%) make between 10,000 and 20,000 yuan. The highest income bracket, above 20,000 yuan, includes 28 respondents (15.2%). For the frequency of Taobao usage, 54 respondents (29.3%) use it very

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frequently, and an equal 54 respondents (29.3%) use it frequently. Meanwhile, 49 respondents (26.6%) use it occasionally, while 24 respondents (13%) use it rarely, and only three respondents (1.6%) never use it. Lastly, 70.7% (130 respondents) reported being interested when asked about interest in Taobao recommendations, while 29.3% (54 respondents) were not.

Table 1: Demographic information

| N=183 | Options | Frequency | Percentage (%) | Cumulative percentage (%) |
|---|---|---|---|---|
| Gender | Male | 82 | 44.8 | 44.8 |
| | Female | 101 | 55.2 | 100.00 |
| Age | <18 | 18 | 9.8 | 9.8 |
| | 18-25 | 36 | 19.7 | 29.5 |
| | 26-30 | 20 | 10.9 | 40.4 |
| | 31-35 | 22 | 12 | 52.4 |
| | 36-40 | 16 | 8.7 | 61.1 |
| | 41-45 | 18 | 9.8 | 70.9 |
| | 46-50 | 21 | 11.5 | 82.4 |
| | >50 | 32 | 17.5 | 99.9 |
| Monthly Income | 0-3000 | 33 | 18 | 18 |
| | 3000-8000 | 56 | 30.6 | 48.6 |
| | 8000-10000 | 36 | 19.7 | 68.3 |
| | 10000-20000 | 29 | 15.8 | 84.1 |
| | >20000 | 29 | 15.8 | 99.9 |
| Frequency of Use | Very Frequent | 50 | 27.3 | 27.3 |
| | Frequent | 56 | 30.6 | 57.9 |
| | Occasional | 50 | 27.3 | 85.2 |
| | Rarely | 24 | 13.1 | 98.3 |
| | Never | 3 | 1.6 | 99.9 |
| Interest in products after browsing on Taobao | Yes | 129 | 70.5 | 70.5 |
| | No | 54 | 29.5 | 100 |
| Total | | 183 | 100 | 100 |

## 4.2. The impact of AI recommendation systems on users' purchase intentions

One of the core goals of an AI recommender system is to increase a user's purchase intent. However, data analysis has shown that recommendation frequency has a significant impact on a user's purchasing behavior. Survey data shows that the probability of a daily recommended purchase is low, while the probability of a recommended purchase is higher at 2-4 times per week. This suggests that while AI recommendations can increase a user's interest in shopping, too frequent recommendations can lead to user fatigue and reduce trust in the recommended products. In the face of high-frequency recommendations, many users will have a feeling of information overload, and even resist the platform's recommendation mechanism. Therefore, appropriately adjusting the recommendation frequency so that it can maintain the user's attention without causing aesthetic fatigue is the key to optimizing the AI recommendation system. Combined with user feedback, the frequency of recommendations 2-4 times a week may be more balanced with user needs, which can maintain the effectiveness of recommendations without appearing too intrusive.

Table 2: Frequency analysis (H1)

| name | Options | Frequency | Percentage (%) | Average value |
|---|---|---|---|---|
| Recommended six times a week (n=134). | Very likely to buy | 20 | 14.93 | 2.46 |
| | Possible to buy | 55 | 41.04 | |
| | So so | 40 | 29.85 | |
| | Unlikely to buy | 16 | 11.94 | |
| | Very unlikely to buy | 3 | 2.24 | |
| Recommended five times a week (n=134). | Very likely to buy | 18 | 13.43 | 2.51 |
| | Possible to buy | 53 | 39.55 | |

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Table 2: (continued)

| | | | | |
|---|---|---|---|---|
| | So so | 42 | 31.34 | |
| | Unlikely to buy | 19 | 14.18 | |
| | Very unlikely to buy | 2 | 1.49 | |
| Recommended four times a week (n=134). | Very likely to buy | 15 | 11.19 | 2.56 |
| | Possible to buy | 52 | 38.81 | |
| | So so | 46 | 34.33 | |
| | Unlikely to buy | 19 | 14.18 | |
| | Very unlikely to buy | 2 | 1.49 | |
| Recommended three times a week (n=134). | Very likely to buy | 13 | 9.70 | 2.69 |
| | Possible to buy | 43 | 32.09 | |
| | So so | 54 | 40.30 | |
| | Unlikely to buy | 20 | 14.93 | |
| | Very unlikely to buy | 4 | 2.99 | |
| Twice a week recommended (n=134). | Very likely to buy | 12 | 8.96 | 2.85 |
| | Possible to buy | 36 | 26.87 | |
| | So so | 53 | 39.55 | |
| | Unlikely to buy | 26 | 19.40 | |
| | Very unlikely to buy | 7 | 5.22 | |
| Recommended once a week (n=134). | Very likely to buy | 13 | 9.70 | 3.02 |
| | Possible to buy | 31 | 23.13 | |
| | So so | 44 | 32.84 | |
| | Unlikely to buy | 32 | 23.88 | |
| | Very unlikely to buy | 14 | 10.45 | |
| total | | 188 | 100.0 | 16.09 |

## 4.3. The impact of shopping goal clarity on the purchase intention of recommended products

The dependent variable is the likelihood of purchasing the recommended products on Taobao's homepage when the user has a clear purchase goal (on a scale of 1-5, with lower values indicating more likely purchases), and the independent variables are the options with different likelihoods of purchasing (Very Likely, Likely, Fair, Unlikely, and Very Unlikely).

Of the 134 respondents, the ‘very likely’ group had the lowest mean (2.28), indicating that they were most likely to purchase the recommended product, while the ‘very unlikely’ group had the highest mean (3.11), indicating that they were least likely to purchase the recommended product, with an overall upward trend in the means, indicating a definite likelihood of purchasing the recommended product. The highest mean value (3.11) in the ‘very unlikely’ group indicates that they are least likely to buy the recommended products, and the overall mean value shows an increasing trend, indicating that users with clear consumption goals are more likely to accept the recommended purchase.

The analysis of variance (ANOVA) results showed an F value of 4.433 and a P value of 0.002 (less than 0.05), indicating that there is a statistically significant difference between different purchase possibilities.

Therefore, this data supports hypothesis two, which states that users are more likely to choose products recommended by the recommender system when they have a clear purchase goal.

Table 3: Analysis (H2)

| Question | Opitions | N | M±SD | F | P |
|---|---|---|---|---|---|
| How likely are you to buy a product recommended on the Taobao homepage when you have a clear purchase goal? | Extremely possible | 47 | 2.28±0.90 | 4.433 | 0.002 |
| | Possible | 43 | 2.75±0.63 | | |
| | Neutrality | 32 | 2.84±0.65 | | |
| | Impossible | 8 | 3.00±0.80 | | |
| | Extremely impossible | 4 | 3.11±0.50 | | |
| | Total | 134 | 2.63±0.79 | | |

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### 4.4. The relationship between Taobao usage behavior and purchase intention

As can be seen from the above table, the correlation analysis is used to study the correlation between purchase intention and Taobao frequency, and the Pearson correlation coefficient is used to express the strength of the correlation. Specifically, it can be seen that the correlation coefficient between purchase intention and frequency of Taobao is -0.259, and shows a significance of 0.01, which indicates that there is a significant negative correlation between purchase intention and frequency of Taobao.

Table 4: Pearson (hypothesis 3)

| | Willingness to buy |
|---|---|
| How often Taobao is used | -0.259** |

* p<0.05 ** p<0.01

Table 5: Linear regression analysis results (hypothesis 3)

| Linear regression analysis results | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Non-normalized coefficients | | Normalization factor | t | p | Colinearity diagnosis | |
| | B | Standard Error | Beta | | | VIF | Tolerance |
| constant | 14.335 | 1.053 | - | 13.610 | 0.000** | - | - |
| How often Taobao is used | -1.505 | 0.489 | -0.259 | -3.077 | 0.003** | 1.000 | 1.000 |
| R 2 | 0.067 | | | | | | |
| Adjust R 2 | 0.060 | | | | | | |
| F | F (1,132)=9.467,p=0.003 | | | | | | |
| D-W values | 1.982 | | | | | | |

Note: Dependent variable = New_ purchase intent
* p<0.05 ** p<0.01

## 5. Discussion

### 5.1. Hypothesis 1

The finding of this study indicates a correlation between the frequencies of personalized recommendations and the purchase intention. This result find that the frequencies of recommendations show a downward line with purchase intention which is different to the research hypothesis that the relationship between increasing frequency of personalized recommendation and purchase intention is inverse U-shape.

There are several possible explanations for these unexpected findings. One potential reason is that the questionnaire designed frequency are too-large which may not be able to show the U-shape. Additionally, the sampling method are snowball sampling which it lead to bias and it might not be representative to a specific population.

### 5.2. Hypothesis 2

The findings of this study support another hypothesis which is that people with clear consumption goal are more likely to make a purchase decision by recommendation of the recommender systems. Participants who had an idea of what they wanted showed a significantly higher tendency to accept suggestions provided by the recommender system. The finding show a strong connection between the consumption goal and the consumer purchase intention which proved the finding of Kim, Kang and Bae: 'The clear consumption goal can have an positive effect to their purchase by the recommendation of PRS.'

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One possible explanation for the finding is that consumer with clear goals use the recommender systems as a tool for efficiency rather than use it for discovery. Unlike the consumer with unclear consumption goals, the goal-oriented consumers may have an expectation to the products, and the recommender systems help them find the most relevant options quickly. The consumer with clear goal will have a positive attitude to the recommender systems and they are more likely to make a purchase decision[15].

Additionally, the findings also emphasis the importance of the trust and perceived accuracy in the recommender systems. As the recommendation is able to match consumers' goals, consumers will perceive the system to be in line with their preferences and thus hold a more positive attitude[15].

### 5.3. Hypothesis 3

The finding results that the high usage of PRS are negatively impacts consumers' purchase intention which is challenge that the PRS always enhance consumer purchase intention, engagement and conversion rate [16].

There are some possible explanations for this result. The over-engagement with PRS may give a feeling of tracking to consumer [15]. It may develop resistance or distrust toward PRS, this action may lead to a result of reducing consumers' purchase intention.

Additionally, the filter bubble make consumer be recommended similar product [5] and lead to a fatigue of PRS. The repeated recommended product can make the consumer have the feeling of frustration and make users less likely to purchase.

### 5.4. Limitations

Despite the finding give several expected results of correlation between PRS and purchase intention, there are some limitations in the study and can be avoid in the future research. This study has a snowball sampling which may lead to a bias and it may not be able to represent for specific populations and the sample size of 183 is relatively small and may not represent the wider population of Taobao users. In the future research, the sample size and the sample method should be designed in a more effective way. And the failure of the hypothesis 1, highlight the complexity of the factors may affect consumer purchase intention. The recommendation frequency options may not have been detailed enough to test the hypothesized inverse U-shaped relationship. Future research should more focus on the design of frequencies and the control of the factors may influence consumers purchase intention. Besides, the individual difference, such as the prior experience with recommender systems or the doubt to the AI-driven systems were not explored in this study. Future research should investigate the conditions in different industries and the interactions to the recommender systems and the trust in AI influenced the decision-making to the goal-oriented consumers. Lastly, as the research focused solely on Taobao, findings may not be applicable to other platforms or industries. Future studies should use larger, more diverse samples and consider more variables to strengthen the results.

## 6. Conclusion

This research shows that personalized recommendations can have a big impact on consumers' buying intentions, but how well they work depends on important things like recommendation frequency, users' familiarity with the platform, the clarity of shopping goals, and income levels.

First, the data shows that it is more likely for users to purchase on items especially when these ideas are daily recommended. Consumers usually trust the platform's algorithm and are more likely to buy when they are receiving the same ideas repeatedly than when they are not. Maintaining a moderate frequency of recommendations, specifically two to four times a week, seems to be the best balance: consumers still like relevant ideas without finding them too annoying.

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For shoppers who have clear goals are more likely to buy things they didn't plan to when they look at ideas; on the other hand, people who do not have a clear goal are less likely to buy things on the spot and look around. In other words, the data suggest that a lack of a clear purchase goal is associated with a reduced tendency to purchase the products recommended on the Taobao homepage.

This study finds an unexpected correlation between personalized recommendation frequencies and purchase intention, not the hypothesized inverse U-shape, likely due to questionnaire design and snowball sampling bias. It supports that consumers with clear goals are more likely to buy via recommendations as they use systems for efficiency. Trust and accuracy in recommenders matter. This research notes limitations like snowball sampling bias and small sample size. Future research should improve sampling, study frequencies, and explore individual differences and industry- specific interactions.

Finally, well-managed personalized recommendations are beneficial. E-commerce platforms can boost buy intent by altering recommendation frequency, and it can also consider user behavior, financial constraints, and balancing new and relevant offerings. Keep an eye on these systems and tweak their algorithms to prevent filter bubbles and user fatigue from damaging them.

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