The Impact of AI personalized Recommendation Scale on Consumer Purchase Decisions

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Abstract. In the rapidly changing digital market, AI-based personalized recommendations significantly enhance consumer shopping experiences and drive business growth. This study investigates how the volume of recommendations (independent variable) influences consumer purchase behavior (dependent variable) through perceived attractiveness (mediating variable) and examines the moderating effect of decision-making style. Based on survey data from 380 online shoppers, the results reveal that perceived attractiveness mediates the relationship between recommendation volume and purchase behavior, while decision-making style positively moderates the effect of recommendation volume on perceived attractiveness. These findings uncover the psychological mechanisms underlying the impact of AI personalized recommendations on consumer behavior, offering valuable guidance for optimizing recommendation systems to improve consumer satisfaction and business outcomes.

Keywords: AI personalized recommendations, Recommendation scale, User perception, Decision-making style, Purchase decision Introduction

1 Introduction

Traditional retail often faces challenges of choice overload, which can reduce satisfaction, complicate decision-making, and lead to purchase abandonment. Chen, M et al.,(2022) noted that product attributes and individual differences significantly influence consumer behavior [1]. In online retail, studies have examined product display styles and layouts, yet the impact of product quantity remains underexplored [2]. Samuel Dodin et al., (2023) found that increasing options elevates search costs, influencing channel selection [3].AI-powered personalized recommendation systems mitigate these issues by curating product lists. The recommendation scale—the number of items presented-significantly affects user perception and decision-making. Liu Xiaoming et al., (2023) highlighted the influence of recommendation inputs, processes, and outputs, including scale, layout, and explanations, on decisions [4]. While studies on recommendation interfaces and choice overload provide insights, the decision-making process remains a "black box" [5].This study explores how AI recommendation scale impacts

M. Zhang et al. (eds.), *Proceedings of the 2025 5th International Conference on Informatization Economic Development and Management (IEDM 2025)*, Advances in Economics, Business and Management Research 330,
https://doi.org/10.2991/978-94-6463-724-3_25

user decisions, using entropy-based analysis and experiments. It examines the scale's influence on perception, decision-making, and moderating effects of decision styles, providing practical insights for optimizing recommendation systems in online retail.

2 Literature Review

Artificial intelligence (AI) personalized recommendation systems are becoming increasingly integral to e-commerce platforms, leveraging user behavior and preference data to dynamically adjust recommendation content and scale, providing more tailored services. In theoretical studies on recommendation systems, the recommendation scale has been identified as a critical factor influencing user decision-making behavior [6]. While larger recommendation scales may lead to choice overload, thereby reducing purchase intention and satisfaction, appropriately sized scales enhance perceived attractiveness and decision efficiency[7]. According to the SOR (Stimulus-Organism-Response) model, recommendation scale acts as a stimulus that influences users' psychological perceptions, such as perceived attractiveness, which subsequently affects their decision-making processes [8]. Knijnenburg et al., (2020) found that short recommendation lists effectively mitigate choice difficulties, while long lists attract users who prioritize comprehensive decision-making [9]. Thus, exploring the dynamic impact of recommendation scale on user perception and decision behavior holds substantial theoretical significance and practical implications for optimizing recommendation system design.

3 Theoretical Analysis and Research Hypotheses

The SOR (Stimulus-Organism-Response) framework suggests that consumers exhibit varying decision responses influenced by psychological perceptions when exposed to different stimuli. Recent studies indicate that features such as the scale and organization of personalized recommendation systems play a crucial role in shaping users' views of the recommendation system, consequently impacting their choices. For instance, research conducted by Chen et al. (2023) revealed that both personalization and the structure of information in recommendation systems influence how users perceive the system, which in turn affects their decision-making processes and results[10]. Furthermore, another study by Liu et al. (2023) demonstrated that cognitive mechanisms alongside individual traits influence the decision-making processes and outcomes, particularly in the context of how context activation and the need for cognition affect these processes[11]. Consequently, this research initially formulates a model examining how the scale of AI personalized recommendations impacts consumer purchasing decisions, as illustrated in Figure 1.

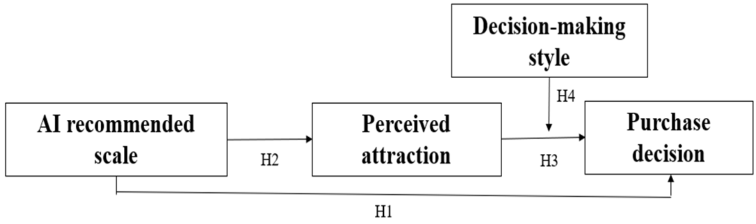

Fig. 1. A Basic Research Model of the Impact of Recommendation Scale on User Perception and Decision Making

The study finds that when the AI recommendation scale expands, users' perceived attractiveness of the recommendation increases, but this attractiveness is counteracted by increased perceived choice difficulty [12]. Moreover, the study by Reutskaja et al., (2020) shows that users' perceptions are influenced by the number of recommended products; when the number of products increases, users' perceived attractiveness of the recommendations initially rises, but when the number of products exceeds the acceptable range, perceived attractiveness decreases[13]. Based on these research findings, this study takes perceived attractiveness as a variable to measure users' psychological perception and proposes the following hypotheses:

H1: *Users' perceived attractiveness varies significantly under different AI recommendation scales.*

Based on the SOR model, when users form a psychological perception of the recommendation scale, they make a judgment on whether to choose from the recommendation set, decide whether to invest time and effort in browsing the recommended products, and finally evaluate the overall decision quality. Additionally, the Howard-Sheth model, one of the three major consumer purchasing behavior models, also emphasizes that psychological perception stimulates users to generate motivation or intention to choose, thereby affecting the effort put into the selection process (decision effort) and the evaluation of the final choice (decision quality)[14]. Therefore, this study first examines the impact of AI recommendation scale on the user decision-making process, hypothesizing that recommendation scale affects choice decisions, and proposes the following hypothesis:

H2: *Users' decision-making varies significantly under different AI recommendation scales.*

Next, the relationship between perceived attractiveness and decision-making processes and the relationship between decision-making processes and outcomes are considered. The study by Maosheng et al., (2023) found that perceived attractiveness positively affects choice satisfaction, i.e., the greater the perceived attractiveness, the higher the choice satisfaction[15]. Combining user decision-making theories and related findings, this study posits that user perception first affects the decision-making process; that is, the greater the perceived attractiveness, the stronger the user's intention to choose, and the more effort they are willing to put in. Subsequently, the decision-making process affects users' final evaluation of decision quality. Based on this, the following research hypothesis is proposed:

H3: *Perceived attractiveness positively affects user decision-making.*

Babak et al.(2022) classified users according to their decision-making styles into maximizers, who pursue the best choices, and satisficers, who seek to avoid risk and satisfy their needs. They found significant differences in users with different decision-making styles when choosing from the same number of products. Maximizers spend more time and effort browsing and seeking more information to make a decision, while satisficers stop browsing once they find a choice that meets their needs[16]. Jiwei Zhu et al.,(2021) considered users' internal characteristics, reflecting personal knowledge and motivation, as a moderating variable between the number of options and decision variables, such as user preferences and decision goals[17], but did not consider the differences in decision-making among users with different styles. Ballesta, S. et al., (2022) studied the impact of choice set presentation order on user search behavior and found that maximization tendency moderates the effect of presentation order on search depth [18]. Andrea et al.,(2022) confirmed in their research on purchase channel decision-making behavior that risk-averse consumers have different sensitivities to product attributes that affect perceived transaction costs[19]. Therefore, this study takes user decision-making style as a moderating variable between perceived attractiveness and decision variables, studying the differences in decision-making among users with different styles, and proposes the following hypothesis:

H4: *Decision-making style moderates the relationship between perceived attractiveness and decision variables.*

4 Experimental Design and Implementation

To uncover the "black box" of the impact of AI recommendation scale on user decisions, this study uses both scenario-based behavioral data and subjective survey data for empirical research.

4.1 Variable Explanation

The explanation and design of key variables are summarized in Table 1.

Table 1. Variable Interpretation and Design.

Variable type	Variable name	Variable interpretation and design
Independent variable	AI recommended scale	**Explanation**: The number of items in the recommended list, is the length of the recommended list. Design: Considering the actual situation of the average product scale of personalized recommendation lists on mainstream platforms, the independent variable recommendation scale refers to Knijnenburg et al. 's division criteria for long and short lists. Based on the pre-test results of the number of recommended products acceptable to users, the recommendation set of 6 products is determined as the short list and the recommendation set of 30 products as the long list.

Dependent variable	Purchase decision	Interpretation: Refers to the subjective evaluation of the user's choice or judgment after deciding, such as satisfaction, possibility of regret, etc. Design: Subjective survey, referring to the maturity scale adopted by Chen Mingliang et al.
Intermediate variable	Perceived attraction	Explanation: Refers to the psychological perceived benefits of users on the scale of recommendations. Design: Subjective survey using maturity scale adopted by Knijnenburg et al., Pu et al.
Regulating variable	Decision-making style	Interpretation: Refers to the characteristics of information processing in the decision-making process of users. Design: Subjective survey, using Turner et al. 's decision style scale for reference.

4.2 Experimental Materials and Subjects

Based on the latest "China Online Shopping Market Research Report" from the China Internet Network Information Center in June 2023, the most commonly purchased product categories by Chinese netizens are clothing, daily necessities, and books and audiovisual products. Referring to the word frequency analysis method based on online review texts by Anindya et al.,(2006) which determines user brand preferences, books, the category with the lowest user preference scores among the three, were chosen as the experimental material[20]. The lowest preference literary work "Alive" was selected as the browsing history for users, and the recommended books displayed in the simulation experiment were chosen from related books recommended by various websites.

To reduce the impact of non-stimulus factors on the experimental effect, especially to control for recommendation diversity, the experiment only presented the recommendation list of literary works. At the same time, referring to the method used by Hu Jiajing et al.(2014) in tourism context choice overload experiments to test the preference differences of subjects[21], the differences in price and preference of the books used as experimental materials were controlled within 20%. Finally, 30 books were selected as the long list of experimental materials. These 30 books were sorted by preference level and divided into 6 groups, with one book randomly selected from each group as the short list of experimental materials. Behavioral experiments and subjective surveys selected college students, who are the main group of online shoppers, and have similar demographic characteristics as subjects.

4.3 Behavioral Experiment

The behavioral experiment adopted a within-subjects design. Using E-prime software to simulate an online shopping scenario and implement the experimental process, personalized recommendation system long and short recommendation lists were randomly presented. The software background recorded the number of items viewed by the subjects, the products selected, decision time, and other behavioral data. Subjects needed to select the books of interest from the recommendations and add them to the shopping cart. After completing the simulated decision task in each scenario, they completed a recall task for the items of interest and a user perception questionnaire for screening purposes. Based on the pre-test, in both long and short recommendation list scenarios, the majority of subjects chose 3 books, accounting for over 53%. Therefore, the experimental task was to choose 3 books from the recommendation list to ensure consistency in the decision task. The behavioral experiment had 73 subjects, with 69 valid subjects completing the task, resulting in a 95% efficiency rate, and 138 valid experimental data points. Reliability analysis results showed that the significance levels of inter-group differences in variables were all greater than 0.05, indicating no significant inter-group effects, suggesting consistent decision-making behavior among the subjects, and the experimental design was reliable.

4.4 Questionnaire Survey

The survey used a 5-point Likert scale[22]. To avoid the continuous influence of cognitive delay effects on the subjects, the formal survey adopted a between-subjects design, with subjects only needing to complete the questionnaire for one scenario. A total of 320 online questionnaires were distributed and recovered, with 134 valid questionnaires in the short list scenario and 145 in the long list scenario, resulting in an efficiency rate of over 87%. The Cronbach's alpha for the subjective survey questionnaire was 0.838>0.8, and the cumulative explained variance percentage of the items for each variable was at least 59.295%>50%, indicating good reliability and validity of the sample data obtained through the measurement items.

5 Discussion and Analysis

5.1 The Impact of AI Recommendation Scale on Perceived Attractiveness and Purchase Decision

Observing whether there are significant differences in the overall distribution of observed variables at different levels of control variables can be analyzed using one-way ANOVA and non-parametric tests. First, the mean values were calculated to transform perceived attractiveness variables and decision variables into manifest variables. The transformed variable data showed that perceived attractiveness and purchase decision variables met the requirement of homogeneity of variance. The one-way ANOVA results are shown in Table 2.

Table 2. One-way ANOVA results of perceived attractiveness and purchase decision

Variable Type	SS	df	MS	F	Sig	Variable Type
Perceived attraction	interclass	1.818	1	1.818	7.017	0.009**
	intra-class	70.232	271	0.259		
	totality	72.051	272			
Purchase decision	interclass	0.012	1	0.012	0.051	0.821
	intra-class	63.090	271	0.233		
	totality	63.102	272			

As shown in Table 2, the significance levels of inter-group differences in perceived attractiveness and choice intention under different AI recommendation scales are $0.009<0.01$ and $0.821>0.05$, respectively, indicating that there are significant differences in users' perceived attractiveness under different recommendation scales, supporting Hypothesis H1. To further understand the specific differences in perceived attractiveness and decision-making under different recommendation scales, descriptive statistical analysis of these variables was conducted, as shown in Table 3.

Table 3. Descriptive statistical results of perceived attractiveness and purchase decision

Variable		N	Mean	SD	SE	Mean (95% CI)	
						lower limit	upper limit
Perceived attraction	Short list	130	3.8973	0.52627	0.04634	3.8056	3.9890
	Long list	145	4.0608	0.49318	0.04110	3.9795	4.1420
Purchase decision	Short list	130	4.0827	0.44882	0.03952	4.0045	4.1609
	Long list	145	4.0694	0.51076	0.04256	3.9853	4.1536

As shown in Table 3, the perceived attractiveness significantly increases when the AI recommendation scale expands. When the significance level of differences in perceived attractiveness, perceived choice difficulty, recall effect, decision time, and search depth under different recommendation scales is $P=0.000<0.001$, it indicates that AI recommendation scale has a significant impact on user decision-making, supporting Hypothesis H1.

Results analysis shows that AI personalized recommendation scale has a significant positive impact on consumer purchase decisions ($\beta=0.71$, $P<0.001$), and perceived attractiveness has a significant positive impact on the effect of AI recommendation scale on purchase decisions ($\beta=0.57$, $P<0.001$), thus verifying Hypothesis H2. To further verify H2, we conducted the following tests.

5.2 Mediating Effect of Perceived Attractiveness

To verify the mediating effect, this study uses Sari (2022) to test the mediating effect. The specific test is conducted using PROCESS 3.3 plugin compiled by Hays (2012)[23,24]. The analysis of the mediating effect of perceived attractiveness between AI recommendation scale and purchase decision shows that the indirect effect of perceived attractiveness between AI recommendation scale and purchase decision is 0.14, with a Bootstrap 95% confidence interval of (0.08, 0.21), not including 0, indicating that the mediating effect of perceived attractiveness between AI recommendation scale and purchase decision is significant, as shown in Table 4, thus verifying Hypothesis H3.

Table 4. Bootstrap Results of Mediating Effect

Effect Type	Effect Value	Boot SE	Bootstrap95% CI		Relative Effect Percentage
			lower	upper	
Total Effect	0.71	0.03	0.66	0.77	100.00
Direct Effect	0.14	0.04	0.06	0.23	19.47
Total Indirect Effect	0.57	0.04	0.50	0.65	80.53
Perceived Attractiveness	0.14	0.04	0.08	0.21	19.52
Purchase Decision	0.43	0.04	0.35	0.52	61.01
Perceived Attractiveness - Purchase Decision	-0.29	0.07	-0.42	-0.15	42.23

5.3 Moderating Effect of Decision-Making Style

To test whether decision-making style moderates the relationship between perceived attractiveness variables and decision variables, the hierarchical regression method proposed by Alaybek, B. et al.(2022) was used for the moderation effect test [25]. Using the short list scenario as an example, the hierarchical regression results are shown in Table 5.

Table 5. Moderation Effect Analysis of Decision-Making Style on Perceived Choice Difficulty and Choice Intention

Independent Variable	Model 1			Model 2		
	β	T	Sig	β	T	Sig
Perceived Attractiveness	-0.202	2.336	0.021*	-0.376	-3.359	0.001**
Decision-Making Style	0.000	0.000	1.000	0.000	0.000	1.000
Perceived Attractiveness × Decision-Making Style				0.267	2.387	0.018*
R2			0.041			0.032
ΔR2						0.041*
F-value			2.728(0.069)			3.785(0.012*)
ΔF-value						1.057

As shown in the table, decision-making style has a significant effect on the relationship between perceived attractiveness and purchase decision. Additionally, the significance of the regression coefficient between the two variables in Model 2, after adding the interaction term, is P =0.001, smaller than the P =0.041 in Model 1, indicating that decision-making style can significantly moderate the relationship between perceived attractiveness and purchase decision in the short list scenario, thus verifying Hypothesis H4.

In summary, the hypothesis testing results and research findings of this study are shown in Table 6.

Table 6. Hypothesis Testing Results

Hypothesis	Result	Content
H1	Supported	Recommendation scale has a significant positive impact on perceived attractiveness.
H2	Partially Supported	Based on subjective survey data, the test is not supported, but different recommendation scales significantly impact decision behavior.
H3	Supported	Perceived attractiveness positively influences decision-making, especially in the short list.
H4	Partially Supported	Decision-making style moderates the relationship between perceived choice difficulty and choice intention in the short list, changing the relationship in the long list.

6 Research Conclusions and Implications

6.1 Research Conclusions

Conclusion 1: The AI recommendation scale impacts perceived attractiveness and immediate decision behavior. Both subjective surveys and behavioral experiments show that as the AI recommendation scale expands, users' perceived attractiveness of the recommendations significantly increases, consistent with the findings of Knijnenburg et al., [9]. Although users' decision behavior changes significantly, subjective surveys show no significant changes in their choice intention, decision effort, or decision quality as the recommendation scale expands. One possible explanation is that users keenly perceive changes in external stimuli, which are reflected in their immediate behavior, such as significantly decreased recall effect, search depth, and increased decision time for the items of interest. However, users' subjective evaluations of their decision behavior, such as choice intention, decision effort, and decision quality, are post-process results of information processing rather than direct responses to external stimulus changes, so their subjective evaluations of decision behavior do not change significantly.

Conclusion 2: The impact of perceived attractiveness on decision-making varies under different AI recommendation scales. A long list can provide more product options and be more attractive to users, making them more willing to put in decision effort. However, the positive impact of perceived attractiveness on decision effort is weakened under the mediation of choice intention, as the perceived attractiveness of a long list does not positively impact choice intention as strongly as a short list. Consequently, the relatively low decision effort results in poorer decision quality, evidenced by the extended decision time, decreased search depth, and poorer recall effect of users under the long list. In contrast, the relatively low perceived choice difficulty in the short list results in higher choice intention. Through the mediation of choice intention, the impact of perceived choice difficulty on decision effort changes from positive to negative. In other words, in the short list scenario, the lower the perceived choice difficulty, the more effort users are willing to put into the decision. Consequently, the relatively high decision effort leads to better decision quality. Behavioral experiment results confirm this.

Conclusion 3: Decision-making style moderates the impact of perceived attractiveness on decision-making. In the short list scenario, the impact of perceived attractiveness on decision intention varies depending on users' decision-making styles. In the long list scenario, the impact of perceived attractiveness on decision-making is significantly moderated by decision-making style. Maximizers, who pursue the best outcomes, are inherently more willing to put in decision effort. The increase in perceived attractiveness stimulates maximizers to put in more decision effort, making the impact of perceived attractiveness on decision effort stronger for maximizers compared to satisficers.

6.2 Practical Implications

Appropriate recommendation scales can improve user experience. Currently, the average length of personalized recommendation lists on mainstream e-commerce platforms is 6. Short lists effectively avoid choice difficulties for users, but compared to long lists presenting richer recommendations, they cannot provide users with stronger attractiveness.

Personalized adjustment of recommendation scale is one of the future optimization goals of personalized recommendation systems. Dongjin Yu. et al. (2022) pointed out that providing differentiated customized services based on users' characteristics can effectively enhance user experience and selection efficiency [26]. Therefore, by modeling user preferences based on personal information, historical transactions, and interaction behavior, and improving user profiling to obtain decision-making style labels, the AI recommendation scale can be adjusted according to users' decision-making styles. Maximizers, who are willing to put in more decision effort to pursue perfection, can be presented with long lists, while satisficers, whose choice intention is greatly influenced by perceived choice difficulty, are more suited to short lists.

6.3 Research Limitations and Prospects

This study conducted a comprehensive empirical study on the mutual influence of personalized recommendation system scale, perceived attractiveness, and user purchase decisions based on scenario experiments and survey data. However, the relationship among the three variables is complex and dynamic. Future research can further reveal the internal mechanisms of this complex dynamic influence from behavioral and neurological perspectives by combining multi-modal data such as eye-tracking, EEG, GSR, and clickstream data from server logs, along with neuroscience experiment analysis, system modeling, and simulation.

Acknowledgment

The completion of this research could not have been achieved without the generous support and assistance from numerous individuals and institutions. First and foremost, I would like to express my special thanks to Professor Liang, who provided invaluable guidance academically and offered me tremendous personal care and support throughout the research process. Additionally, I am grateful to Dr. Chen and Dr. Li for their professional guidance and advice on research methods and data analysis. Their expertise and precise critiques significantly enhanced the quality of the research. Furthermore, I would like to thank all the survey participants who were willing to share their personal experiences and information; their participation was crucial to the successful completion of this research. Lastly, I would like to thank my family for their understanding and support; their encouragement has been a strong pillar throughout my research journey.

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