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How Do Personalized Recommendation Systems Influence Consumer Purchase Intention? The Mediating Role of Perceived Value

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Abstract

With the continuous growth of the number of products and user behavior data on e-commerce platforms, personalized recommendation systems have become an important tool connecting information filtering and consumption decisions. This study revolves around the following five parts: 1) Research Background: Existing research focuses primarily on algorithm accuracy; how consumers form value judgments requires further explanation. 2) Research Objectives: To examine how the personalization, accuracy, and timeliness of a recommendation system influence purchase intention through perceived value. 3) Research Methods: Based on a stimulus-organism-response model, 340 questionnaires were used to conduct reliability, validity, correlation, regression, and Bootstrap mediation tests. 4) Research Results: All three system characteristics significantly enhanced perceived value, with personalization having the largest standardization effect (Beta=0.412). Perceived value significantly promoted purchase intention (Beta=0.905). The three indirect effects were 0.442, 0.476, and 0.480, respectively, with 95% confidence intervals not including 0. 5) Research Conclusions: Perceived value played a partial mediating role in all three relationships, indicating that for a recommendation system to achieve purchase conversion, it cannot only pursue technical matching but also needs to ensure that consumers genuinely feel the recommendations are useful, timely, and meet their needs.

Keywords: *Personalized recommendation system, perceived value, purchase intention, S-O-R model, mediating effect*

1. Introduction

With the expansion of product supply on e-commerce platforms, consumers are no longer just facing "more choices," but rather how to find products that meet their needs within a limited time. Recommendation systems, filtering content through browsing, searching, and purchasing records, have transformed from auxiliary tools into crucial facilities influencing browsing and transactions. Research based on platform behavior data has found that adopting recommendation systems increases consumers' session frequency and purchase intensity, but does not necessarily shorten information processing time, indicating that recommendation effectiveness cannot be measured solely by backend accuracy (Feng et al., 2024). The relevance of personalized recommendations is also related to platform revenue and consumers' willingness to pay (Basu, 2021).

However, the ability of an algorithm to generate recommendations does not necessarily mean that consumers will accept them. Recent research shows that transparency, accuracy, novelty, and diversity collectively affect recommendation quality, which in turn influences attitudes, trust, and purchase intention (Nguyen & Nguyen, 2024). Other studies, placing recommendation accuracy, timeliness, and interaction methods within the same framework, have found that personalized recommendations influence purchase intention through flow experience and perceived trust (Yun & Chun, 2024). Therefore, there is still a gap between system metrics and purchase responses due to consumers' subjective judgment.

This study summarizes this judgment as perceived value, which is the consumer's overall evaluation of the benefits brought by recommendations versus the costs such as time and effort. Research in fashion e-commerce has found that the quality of the recommendation system can enhance perceived value, and perceived value plays a mediating role in the influence of recommendation quality on purchase intention (Lo et al., 2026). Cross-border e-commerce research also shows that increased perceived value enhances purchase intention, while shopping risk weakens this intention (Wang et al., 2023).

The stimulus-organism-response (S-O-R) framework connects the external environment, the individual's internal state, and behavioral responses. In AI-enabled value co-creation, prior research has treated perceived personalization and other AI-related perceptions as stimuli and consumer engagement as the organism-level mediator linking those stimuli to value co-creation behavior (Wen et al., 2022). In this paper, recommendation system characteristics belong to the stimulus (S), perceived value belongs to the internal state (O), and purchase intention belongs to the response (R).

Similar research has found that environmental features such as personalization in social commerce influence purchase intention through customer interaction and perceived value (Liu et al., 2021). Recommendation tags also alter online purchase intention through two psychological processes: social proof and risk avoidance (Xu et al., 2023). However, further testing is needed to integrate personalization, accuracy, and timeliness into the same model and compare their independent effects on perceived value.

2. Research Objectives

This study sets three data-testable objectives: First, to identify the impact of personalization, accuracy, and timeliness on perceived value and compare the strength of their effects; second, to test the predictive effect of perceived value on purchase intention; and third, to verify whether perceived value has a mediating effect between the three recommendation features and purchase intention, and based on this, to propose optimization suggestions for e-commerce platforms.

3. Materials and Methods

3.1 Theoretical Framework and Research Hypotheses

Personalization represents the system's ability to provide differentiated content based on users' unique preferences; accuracy represents the degree to which recommended products match current search, browsing, or shopping needs; timeliness represents whether the system can update results promptly based on recent behavior and market changes. Explaining the recommendation source can increase perceived credibility, while the effect of personalized recommendations on website attitude varies by product type (Kim, 2024). Furthermore, perceived personalization predicts value co-creation intention in website-based shopping but not in augmented-reality shopping; in the augmented-reality group, trust and risk mediate this relationship (Alimamy & Gnoth, 2022). Figure 1 shows the research model.

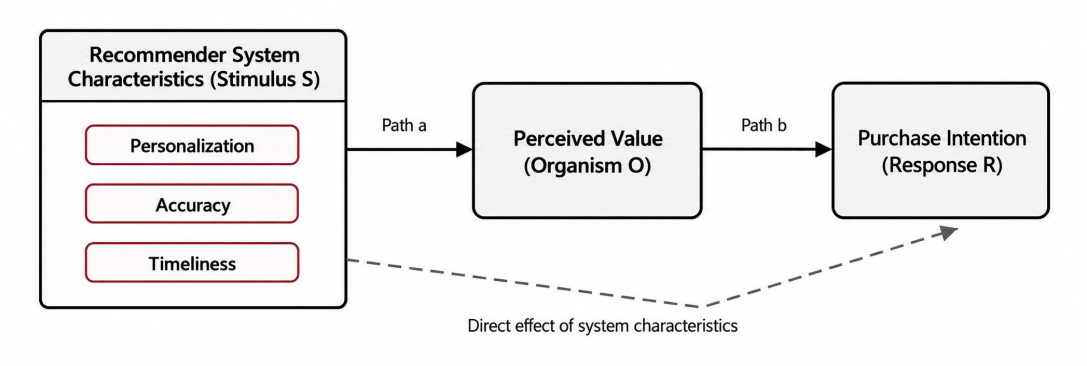


Figure 1 Research Model.

The following models are proposed: H1-H3: Personalization, accuracy, and timeliness positively influence perceived value; H4: Perceived value positively influences purchase intention; H5-H7: Perceived value mediates the relationships between personalization, accuracy, timeliness, and purchase intention. The model also retains the direct path from system characteristics to purchase intention to distinguish between complete and partial mediation.

3.2 Variable Measurement

The questionnaire includes five variables: personalization, accuracy, timeliness, perceived value, and purchase intention. Each variable has four items, for a total of 20 core items, all using a five-point Likert scale, where 1 represents "completely disagree" and 5 represents "completely agree." Personalization items focus on whether recommendations provide customized content based on personal interests and whether they reflect unique tastes; accuracy items focus on whether recommendations match current browsing, searching, and shopping needs; timeliness items focus on whether results are updated based on recent behavior and whether new products and trending content are presented promptly.

The perceived value items were measured from four aspects: shopping efficiency, useful information, decision quality, and shopping experience. The purchase intention items examined whether respondents would purchase unplanned items based on recommendations, whether recommendations influenced their final choice, whether they were willing to add items to their cart or favorite them, and whether they prioritized browsing recommended products.

3.3 Data Collection and Sample

The questionnaire was distributed online through "Wenjuanxing" (a survey platform), lasting 15 days, primarily through WeChat official accounts and three target user communities. A total of 340 usable questionnaires were collected. 215 respondents were male (63.2%), and 125 were female (36.8%). Respondents aged 18-25 and 26-35 accounted for 35.6% and 35.0% respectively, indicating a predominantly young population. 291 respondents (85.6%) reported using e-commerce platforms such as Taobao, JD.com, and Pinduoduo. This structure indicates a high degree of contact between the sample and online shopping scenarios, but it also means that the research conclusions mainly reflect young internet users.

3.4 Data Analysis

Data were analyzed using SPSS. First, Cronbach's alpha test was used for internal consistency, and KMO and Bartlett's test of sphericity were used to determine if the data were suitable for further analysis. Second, Pearson correlation coefficients were calculated. Third, a multiple linear regression model was established to compare the independent effects of the three recommendation features on perceived value, and a regression model was built to predict purchase intention based on perceived value. Finally, 5000 bootstrap sampling was used to test for indirect effects; a mediation effect was considered significant if the 95% confidence interval did not include 0. The mediation model controlled for gender, age, and whether an e-commerce platform was used.

The analysis did not directly equate significant correlation with causation. In particular, the three recommendation features may vary simultaneously in user experience, and the regression coefficients need to be interpreted in conjunction with collinearity diagnostics and research design.

4. Results Analysis and Discussion

4.1 Sample Structure Analysis

A total of 340 valid questionnaires were obtained in this study. Table 1 shows that 215 respondents were male (63.2%) and 125 were female (36.8%). The ages were mainly concentrated in the 18-25 and 26-35 age groups, with 121 and 119 respondents respectively, totaling 70.6%. Regarding platform usage, 291 respondents (85.6%) had experience using e-commerce platforms such as Taobao, JD.com, and Pinduoduo. Therefore, most respondents were familiar with product recommendations, browsing history, and recommendation pages, and were able to answer the questionnaire based on their daily shopping experience.

Table 1 Basic Characteristics of Respondents (N=340)

Statistical dimensions	Category	Number of people	Proportion
Gender	Male	215	63.2%
Gender	Female	125	36.8%
Age	Under 18 years old	24	7.1%
Age	18-25 years old	121	35.6%
Age	26-35 years old	119	35.0%
Age	36-45 years old	75	22.1%
Age	46 years and older	1	0.3%
E-commerce platform use	Used	291	85.6%
E-commerce platform use	Never used	49	14.4%

The sample primarily consists of young users who frequently use mobile internet and online shopping, which is beneficial for respondents to answer based on their actual recommendation experiences, but also limits the extrapolation of conclusions. Only one respondent was 46 years of age or older; therefore, the conclusions of this paper are mainly applicable to this online youth sample.

The proportion of males was 26.4 percentage points higher than that of females. Although the mediation test controlled for gender, age, and e-commerce platform usage experience, the controlled variables cannot completely eliminate sampling bias; the results in this paper should still be limited to this sample and self-reported data.

4.2 Reliability and Validity Testing

The questionnaire's 20 core items measure personalization, accuracy, timeliness, perceived value, and purchase intention, with each variable containing four items. Table 2 summarizes the internal consistency and factor analysis applicability indicators. The Cronbach's Alpha for the five subscales ranged from 0.886 to 0.912, all above 0.70, indicating good internal consistency among items under the same variable. The personalized scale had the highest coefficient at 0.912; accuracy and timeliness were both 0.886; perceived value and purchase intention were 0.896 and 0.889, respectively.

Table 2 Results of Scale Reliability and Validity Tests

Test	Object or statistic	numerical values	Judge
Cronbach's Alpha	Personalization	0.912	Good internal consistency
Cronbach's Alpha	accuracy	0.886	Good internal consistency
Cronbach's Alpha	Timeliness	0.886	Good internal consistency
Cronbach's Alpha	Perceived Value	0.896	Good internal consistency
Cronbach's Alpha	Purchase intention	0.889	Good internal consistency
Cronbach's Alpha	Total Table	0.997	High overall consistency
KMO	Sampling appropriateness	0.984	Suitable for factor analysis
Bartlett's test of sphericity	Approximate Chi-square	7181.141	Significant
Bartlett's test of sphericity	Degrees of freedom	190	—
Bartlett's test of sphericity	Significance	<0.001	Reject the identity matrix hypothesis

The total scale alpha is 0.997, indicating high overall consistency, but this value may be related to the similarity of item descriptions. Considering the high correlation coefficients discussed later, reliability assessment should primarily rely on the results of the five subscales, and the total scale coefficient should not be simply interpreted as indicating complete differentiation of constructs.

The KMO value is 0.984; the Bartlett's test of sphericity approximates a chi-square value of 7181.141 with 190 degrees of freedom and $p < 0.001$, indicating that the data is suitable for further analysis. However, the KMO and Bartlett's test alone cannot prove complete differentiation of the five constructs; correlation coefficients and collinearity indicators are still needed for judgment.

4.3 Correlation Analysis

Pearson correlation analysis is used to observe the degree of unidirectional change between variables. Table 3 shows that all five variables are significantly positively correlated pairwise, and all are significant at the 0.01 level. Regarding the main research pathways, the correlation coefficients between personalization, accuracy, and timeliness and perceived value were 0.912, 0.899, and 0.896, respectively; the correlation coefficients between these three system characteristics and purchase intention were 0.903, 0.896, and 0.895, respectively; and the correlation coefficient between perceived value and purchase intention was 0.905. The correlation directions are consistent with the theoretical expectations of H1–H7.

Table 3 Pearson Correlation Coefficients of the Main Variables

Variable	Alpha	1	2	3	4	5
1. Personalization	0.912	1				
2. Accuracy	0.886	0.911**	1			
3. Timeliness	0.886	0.900**	0.900**	1		
4. Perceived Value	0.896	0.912**	0.899**	0.896**	1	
5. Purchase Intention	0.889	0.903**	0.896**	0.895**	0.905**	1

Note: ** $p < 0.01$.

These results indicate that consumers often consider "whether it's designed for me," "whether it meets my needs," and "whether it's updated promptly" as interconnected experiential judgments. A good recommendation typically demonstrates understanding the user, matching needs, and timely updates simultaneously.

However, the correlation coefficients of all independent variables are above 0.900. Correlation analysis can only confirm synchronous changes in variables; it cannot prove causation or directly determine which characteristic is most important. Relative effects need to be explained by combining multiple regression coefficients and VIF.

4.4 Regression Analysis of Recommendation System Characteristics on Perceived Value

To compare the independent effects of the three recommendation characteristics, perceived value was used as the dependent variable, and personalization, accuracy, and timeliness were simultaneously included in a multiple linear regression. The model's R^2 was 0.871, the adjusted R^2 was 0.870, and the F-value was 758.883, with a significance level less than 0.001. This indicates that the three variables can jointly explain 87.1% of the variation in perceived value, and the model as a whole reaches a significant level. The high explanatory power is consistent with the results of the correlation analysis, also indicating a close relationship between perceived value and the recommendation experience.

Table 4 Regression results of perceived value prediction based on recommendation system characteristics

Predictor variables	B	SE	Standardized coefficient	t	p	Tolerance	VIF
Constant	0.078	0.074	—	1.065	0.288	—	—
Personalization	0.414	0.053	0.412	7.783	<0.001	0.136	7.336
Accuracy	0.272	0.054	0.266	5.042	<0.001	0.137	7.291
Timeliness	0.292	0.051	0.285	5.695	<0.001	0.152	6.563

Note: The dependent variable is perceived value; $R^2 = 0.871$, adjusted $R^2 = 0.870$, $F = 758.883$, $p < 0.001$.

After controlling for the other two recommendation characteristics, the unstandardized coefficient for personalization was 0.414, the standardized coefficient was 0.412, and the t-value was 7.783; the unstandardized coefficient for accuracy was 0.272, the standardized coefficient was 0.266, and the t-value was 5.042; the unstandardized coefficient for timeliness was 0.292, the standardized coefficient was 0.285, and the t-value was 5.695. The significance of all three coefficients was less than 0.001, supporting H1, H2, and H3. Based on the standardized coefficients of this sample, the independent effect of personalization is relatively large, followed by timeliness, and then accuracy.

The relatively large personalization coefficient indicates that consumers not only care about whether the recommendations are generally accurate, but also whether the system understands their interests and shopping habits. Timeliness remains significant, indicating that outdated recommendations weaken current value. The small accuracy coefficient does not mean it is unimportant; rather, when all three highly correlated variables are included in the model, the variation that can be individually attributed to accuracy is relatively small. All three coefficients are positive and reach $p<0.001$, therefore, it is more important to emphasize their combined effect rather than interpreting small coefficient differences as fixed rankings. This result is consistent with recent evidence that recommendation accuracy, timeliness, and quality jointly influence purchase responses (Nguyen & Nguyen, 2024; Yun & Chun, 2024).

The VIF of the three independent variables is 6.563-7.336, indicating significant collinearity. High collinearity does not automatically negate the overall significance of the model, but it makes individual coefficients more sensitive to sample and item settings.

4.5 Regression Analysis of Perceived Value on Purchase Intention

The second set of regressions uses purchase intention as the dependent variable to examine whether consumers' value judgments can be translated into purchase inclination. Table 5 shows that the non-standardized coefficient of perceived value is 0.901, the standard error is 0.023, the standardized coefficient is 0.905, the t-value is 39.169, and the significance level is less than 0.001. The model R^2 and adjusted R^2 are both 0.819, and the F-value is 1534.216. Therefore, H4 is supported: when consumers believe that recommendations save time, provide useful information, improve decision-making, and bring a better experience, their willingness to browse, save, add to cart, or prioritize recommended products will increase.

Table 5 Regression Results of Perceived Value Predicting Purchase Intention

Variable	B	SE	Standardized coefficient	t	p
Constants	0.308	0.083	—	3.724	<0.001
Perceived Value	0.901	0.023	0.905	39.169	<0.001

Note: The dependent variable is purchase intention; $R^2 = 0.819$, adjusted $R^2 = 0.819$, $F = 1534.216$, $p < 0.001$.

The standardized coefficient of 0.905 and the 81.9% explanatory power indicate that perceived value is the core variable connecting recommendation experience and purchase intention. In this study, perceived value includes efficiency, useful information, decision quality, and pleasurable experience; therefore, the coefficient reflects a comprehensive value judgment, rather than a single price benefit. Similar relationships are observed in online customization and cross-border e-commerce scenarios: when consumers feel the experience or product is more valuable, their purchase intention increases (Ettis & Sellami, 2025; Wang et al., 2023).

However, since both variables are from the same time period and the same questionnaire, and both items involve shopping assistance provided by recommendations, common methodological bias may inflate the coefficient. The results support a stable positive statistical relationship but cannot replace real orders or experimental data.

4.6 Mediation Effect Test of Perceived Value

Regression analysis confirmed the relationship between system characteristics and perceived value, and between perceived value and purchase intention. The mediation test further answers how the influence occurs. A bootstrap sampling of 5000 times was used, controlling for gender, age, and whether or not an e-commerce platform was used. The judgment criterion was whether the 95% confidence interval of the indirect effect contained 0. Table 6 shows that the confidence intervals of the indirect effects of personalization, accuracy, and timeliness did not contain 0, and all three mediation paths reached a significant level.

Table 6 Bootstrap Mediation Effect of Perceived Value

Antecedent variables	Total effect	direct effects	Indirect effects	Indirect SE	Indirect effect 95% CI	Indirect proportion	In conclusion
Personalization	0.905	0.463	0.442	0.051	[0.343, 0.541]	48.8%	Some agents
Accuracy	0.914	0.438	0.476	0.051	[0.381, 0.583]	52.1%	Some agents
Timeliness	0.913	0.434	0.480	0.049	[0.384, 0.577]	52.6%	Some agents

Note: Bootstrap sampled 5000 times, controlling for gender, age, and e-commerce platform usage experience.

The total effect of personalization was 0.905, with a direct effect of 0.463 and an indirect effect of 0.442. The 95% CI was [0.343, 0.541], with the indirect effect accounting for 48.8%. When consumers feel recommended "tailored to them," part of their purchase intention comes from the direct response of being understood, and the other part comes from the value judgment formed by shopping efficiency and information quality. The two parts have similar effects, indicating that the platform needs to improve the matching experience and also let consumers see actual benefits. Both direct and indirect effects are significant, belonging to partial mediation.

The total effect of accuracy was 0.914, with a direct effect of 0.438 and an indirect effect of 0.476. The 95% CI was [0.381, 0.583], with the indirect effect accounting for 52.1%. Accurate matching reduces invalid comparisons and provides a basis for decision-making; these benefits, once perceived, further shape purchase intention. The indirect effect is slightly larger than the direct effect, indicating that accuracy needs to be translated into a "useful" experience by consumers to be fully effective; the direct effect remains significant and also constitutes partial mediation.

The total effect of timeliness is 0.913, the direct effect is 0.434, and the indirect effect is 0.480, with a 95% CI of [0.384, 0.577], and the indirect effect accounts for 52.6%. Timely updates avoid continuing to recommend purchased, lost-of-interest, or out-of-season products, mainly by increasing current value. Among the three paths, timeliness has the highest indirect share, indicating that "appearing at the right time" depends particularly on consumers' judgment of current use; the direct effect remains significant, thus also constituting partial mediation.

These three paths suggest that recommendation systems should not only focus on completing the matching in the background but also ensure that consumers actually feel that the recommendations save time, reduce selection costs, and improve decision-making. Recent research has also found that perceived value connects the platform environment or recommendation system quality with purchase intention (Liu et al., 2021; Lo et al., 2026). 4.7 Summary of Hypothesis Testing

Table 7 maps the preceding analysis to the seven research hypotheses. H1-H3 were tested using the perceived value regression model, H4 using the purchase intention regression model, and H5-H7 using Bootstrap mediation analysis. All seven hypotheses were supported. The first three hypotheses indicate that systematic stimuli can alter consumers' internal value judgments, the fourth indicates that internal judgments can be translated into behavioral intentions, and the latter three connect the two relationships.

Table 7 Results of Hypothesis Testing

Assumption	Relation	Key statistical evidence	Result
H1	Personalization → Perceived Value	Standardization coefficient = 0.412, p < 0.001	Support
H2	Accuracy → Perceived Value	Standardization coefficient = 0.266, p < 0.001	Support
H3	Timeliness → Perceived Value	Standardization coefficient = 0.285, p < 0.001	Support
H4	Perceived value → Purchase intention	Standardization coefficient = 0.905, p < 0.001	Support
H5	Personalization → Perceived Value → Purchase Intent	Indirect effect = 0.442, CI does not contain 0.	Support
H6	Accuracy → Perceived Value → Purchase Intention	Indirect effect = 0.476, CI does not include 0.	Support
H7	Timeliness → Perceived Value → Purchase Intention	Indirect effect = 0.480, CI does not include 0.	Support

Seven hypotheses form a continuous chain of evidence: three system properties enhance perceived value, perceived value enhances purchase intention, and approximately half of the total effect of the three properties is transmitted through perceived value. Direct effects persist, indicating that perceived value is a key but not the only mechanism. All seven hypotheses are supported, but high correlation, homologous questionnaires, and cross-sectional designs may enhance path coefficients. Therefore, this study is suitable for demonstrating stable relationships and significant transmission effects among variables.

4.8 Theoretical Interpretation of Results

The results support the logic of "technical properties—psychological perception—behavioral intention." Recommendation systems provide external stimuli with personalization, accuracy, and timeliness. Consumers do not passively receive output but first judge whether the recommendation can save time, provide information, and improve the experience, subsequently forming a purchase intention. The mediating outcome transforms this internal judgment from conceptual inference into a testable path. This aligns with the recent application of S-O-R in AI contexts, where psychological states transmit the influence of technological stimuli (Wen et al., 2022).

The three properties respectively answer "Is it suitable for me?", "Is the judgment correct?", and "Does it appear when needed?". Personalization has a relatively high independence coefficient; accuracy and timeliness have a slightly higher proportion of intermediaries. These three factors are not substitutes, but rather collectively constitute an acceptable recommendation service.

4.9 Management Implications

First, platforms should shift their focus from "increasing recommendation exposure" to "improving perceived help." Personalization should integrate recent behavior and proactive feedback, and allow users to modify interests, block categories, or retrain preferences. Research shows that perceived usefulness and trust in AI retail platforms jointly influence purchase intention (ElSayad & Mamdouh, 2024).

Second, accuracy and timeliness need to be coordinated. Continuing to display purchased, out-of-season, or expired promotions reduces value, while prioritizing rapid updates while neglecting matching increases the filtering burden. Personalized recommendations do not necessarily mitigate the negative impact of cognitive effort on loyalty; platforms still need to reduce duplicate and invalid information (Hallikainen et al., 2022).

Third, platforms should directly observe perceived value, rather than relying solely on click-through rates to represent effectiveness. A single click out of curiosity may not indicate a useful recommendation, and repeated skipping may suggest an outdated profile. Platforms can combine "helpful," "favorites," "skipped," "not interested," post-purchase reviews, add-to-cart rates, and repeated blocking rates, and observe these metrics grouped by user stage and product type to determine whether recommendations truly reduce selection costs.

Fourth, recommendation explanations and privacy controls should be provided simultaneously. Explaining the recommendation source can increase perceived credibility, while the effect of personalized recommendations on website attitude varies by product type (Kim, 2024). Platforms should also clearly define the purpose of data and methods for disabling personalization. Evidence further shows that perceived personalization predicts value co-

creation intention in website-based shopping but not in augmented-reality shopping; in the augmented-reality setting, trust and risk mediate this relationship (Alimamy & Gnoth, 2022).

5. Conclusion

Based on 340 questionnaires, this study examined the relationship between personalized recommendation system characteristics, perceived value, and purchase intention. The results show that personalization, accuracy, and timeliness all significantly enhance perceived value, with personalization exhibiting a relatively large standardized coefficient in the multiple regression. Perceived value significantly enhances purchase intention and plays a partial mediating role between the three system characteristics and purchase intention. These three indirect effects account for approximately 48.8%–52.6% of the total effect. Theoretically, recommendation systems do not directly drive purchases; their effect depends on consumers' value judgments. Practically, platforms cannot simply optimize offline algorithm metrics; they must also translate personalization, accuracy, and timeliness into an understandable, controllable, and truly useful recommendation experience.

This study also has limitations. First, the sample primarily consisted of users aged 18-35, obtained through online channels; its applicability to middle-aged and elderly consumers and users from different cultural backgrounds still needs to be tested. Second, the study used a cross-sectional self-report questionnaire, measuring perceived value and purchase intention simultaneously, which cannot replace actual purchase data and makes it difficult to completely eliminate common methodological bias. Third, the correlation coefficients among the variables are high, with VIFs ranging from 6.563 to 7.336, indicating that the distinction between the three system characteristics still requires more rigorous measurement and testing. Future research could expand the regional and age samples, combining behavioral logs, experiments, and longitudinal data to examine actual clicks, add-to-cart activity, and purchases, and incorporate transparency, privacy, and perceived risk to compare differences among users of different products, platforms, and countries.

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