# The Impact of AI-Powered Recommendation System Attributes on Consumer Purchase Intention: The Mediation Effect of Perceived Value

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## Abstract

In the context of the rapid growth of artificial intelligence, AI-based recommender systems have become increasingly important in e-commerce and content platforms and, over time, have become a key factor shaping consumers' choices. In accordance with the Stimulus-Organism-Response (S-O-R) model, this paper examines how AI recommender system attributes influence purchase intention through consumer perception. In particular, AI recommender systems are conceptualized as having three core features: predictive capability, accuracy, and dynamism and adaptability. Perceived value is introduced as a mediator variable and is further subdivided into functional value, emotional value, and cognitive value. Data was gathered through a questionnaire survey and processed empirically using SPSS and PROCESS. It was found that all three characteristics of AI recommender systems have strong positive impacts on consumers' purchase intention, while perceived value plays a partial mediating role. Of these, functional value has the highest explanatory power in consumer decision-making. The research contributes to the existing literature on AI recommender systems by considering the psychological processes behind their implementation and offers useful insights into the effective recommendation strategies for digital platforms.

***Keywords***: *AI-based Recommender System, Perceived Value, Consumer Purchase Intention*

## 1. Introduction

With the rapid development of artificial intelligence technology, digital consumption and the e-commerce industry have undergone major changes. Traditional recommendation models based on rules and collaborative filtering have gradually been replaced by AI-driven intelligent recommendation models. AI-based recommender systems have become core infrastructure for digital platforms. According to industry data, about 35% of Amazon's sales and more than 30% of Alibaba's "Double 11 Global Shopping Festival" transactions are driven by recommender systems. Platforms such as ByteDance and JD.com also regard AI recommendation as a core source of competitiveness. However, the industry still generally faces a problem: platforms pay excessive attention to algorithmic indicators and click-through rates, while ignoring users' subjective experiences and psychological feelings. This causes a disconnection between technological investment and commercial conversion. From the perspective of academic research, existing literature remains insufficient in discussing how technical attributes of AI-based recommender systems influence consumer behavior. Most studies focus on algorithm optimization and system performance, while fewer studies analyze, from the perspective of consumers' subjective feelings, the mechanism through which technical attributes are transformed into psychological value.

Consumption decision-making under AI-based recommendation is essentially a transmission process of "technological stimulus-psychological cognition-purchase behavior." Stimulus–Organism–Response (S-O-R) theory provides a relatively complete analytical framework for studying this process. Although many existing studies have used this theory to examine e-commerce behavior, most of them regard recommender systems as static filtering mechanisms. They lack research that matches the technical characteristics of artificial intelligence. For this reason, this study introduces Zeithaml's perceived value theory, establishes a theoretical analysis model suitable for AI recommendation contexts, and further analyzes the influence of technical characteristics on users' purchase intentions.

Based on S-O-R theory, this study starts from three dimensions: predictive capability, accuracy, and dynamism. It takes perceived value as the mediating variable and constructs the mechanism of "AI-based recommendation attributes → perceived value → consumer purchase intention." This provides empirical support for e-commerce platforms in optimizing recommendation strategies. Based on this point, this article proposes the following research questions:

RQ1: What effects do the attributes of AI-based recommender systems have on perceived value?

RQ2: What effects do the attributes of AI-based recommender systems have on consumer purchase intention?

RQ3: What effect does perceived value have on consumer purchase intention?

RQ4: Does perceived value play a mediating role in the influence of AI-based recommender system attributes on purchase intention?

## 2. Objectives

Based on the research motivation above, the objectives of this study are as follows:

1) To explore the effects of predictive capability, accuracy, and dynamism of AI-based recommender systems on consumers' perceived valueBegin with an action verb to describe the behavior at the appropriate level of learning.
2) To test the direct effect of the core attributes of AI-based recommender systems on consumer purchase intention
3) To analyze the positive effect of consumers' perceived value on their purchase intention
4) To verify the mediating effect of perceived value between AI-based recommender system attributes and consumer purchase intention

## 3. Literature Review

1) The relationship between the attributes of AI-based recommender systems and consumer purchase intention

Artificial intelligence has developed recommender systems from static matching tools into intelligent tools with predictive capability, dynamism, and accuracy. These systems can identify users' potential interests and improve user experience. Regarding accuracy, higher accuracy reduces search costs and speeds up decision-making. Herlocker et al. (2004) pointed out that recommendation accuracy is positively related to satisfaction. He et al. (2017) found that the improvement in accuracy brought by deep learning strengthens user trust. Regarding predictive capability, Covington, Adams, and Sargin (2016) argued that a good prediction model can improve click-through rates and viewing duration, and help discover users' potential needs. Regarding dynamism, Hidasi et al. (2015) showed that sequence modeling can capture changes in interests and make the system more responsive. In summary, this paper argues that AI recommendation attributes have a direct positive effect on purchase intention.

H1: AI-based recommender system attributes have a significant positive effect on consumer purchase intention.

2) The relationship between AI-based recommender system attributes and perceived value

This study is based on the Theory of Consumption Values proposed by Sheth, Newman, and Gross (1991). Combined with the AI recommendation context, it selects three dimensions: functional value, emotional value, and epistemic value. According to S-O-R theory, AI recommendation attributes, as external stimuli, influence perceived value through different paths. Accuracy and predictive capability improve the fit of recommendations and enhance functional value, including usefulness and efficiency. Dynamism allows users to perceive that the system understands changes in their preferences, thereby improving epistemic value, including novelty and sensitivity. Suitable recommendations bring a feeling of being understood and stimulate emotional value, such as pleasure. Therefore, AI-based recommender system attributes positively influence perceived value.

H2: AI-based recommender system attributes have a significant positive effect on perceived value.

3) The relationship between perceived value and consumer purchase intention

Based on Zeithaml's (1988) perceived value theory, value is an overall subjective evaluation based on the "get-give" trade-off and is a premise of purchase motivation. Dodds, Monroe, and Grewal (1991) further pointed out that when perceived value is greater than cost, purchase likelihood increases significantly. In the field of information technology, Pavlou (2003) found that perceived value is an important determinant of online shopping. In AI recommendation contexts, the system does not directly sell products, but provides "information value." Whether consumers are willing to adopt recommendations depends on whether they feel the recommendations are "worthwhile." Harper and Konstan (2015) emphasized that the core function of recommender systems is to help users discover new things, which is an important driving force. Li and Karahanna (2015) pointed out that under AI recommendation, consumers' value cognition comes more from subjective feelings such as enjoyment, exploration, and understanding of intelligent technology. These factors directly influence purchase intention.

H3: Perceived value has a significant positive effect on consumer purchase intention.

4) The mediating role of perceived value

According to S-O-R theory, external stimuli influence behavior through individuals' internal feelings. The influence of AI-based recommender system attributes on purchase intention should be mediated by perceived value, which is the "O" variable in the model. Existing studies have confirmed that "value → behavior" is a core mechanism in e-commerce and recommender systems. Pavlou (2003) pointed out that technical characteristics need to influence purchase behavior through value evaluation. Venkatesh et al.'s (2003) Unified Theory of Acceptance and Use of Technology (UTAUT) shows that the effect of technical characteristics on behavioral intention is based on "performance expectancy," which is a form of value judgment. Harper and Konstan (2015) emphasized that only recommendations considered "valuable" are likely to promote purchase.

H4: Perceived value plays a mediating role in the influence of AI-based recommender system attributes on purchase intention.

Based on S-O-R theory, this study constructs an influence mechanism model of AI-based recommender systems using the framework of "stimulus-organism-response." In this model, the attributes of AI-based recommender systems, including accuracy, predictive capability, and dynamism, serve as external environmental stimuli (S). Perceived value, including functional value, emotional value, and epistemic value, serves as the individual's internal organism state (O). Consumer purchase intention serves as the behavioral response (R). The model assumes that AI recommendation attributes positively influence consumer purchase intention (H1) and indirectly influence purchase intention through the mediating role of perceived value (H4). At the same time, AI recommendation attributes positively influence perceived value (H2), and perceived value positively influences purchase intention (H3). This model reveals how technical characteristics are transformed into purchase motivation through users' value cognition in AI recommendation contexts. It provides an integrated analytical framework for understanding the influence of intelligent recommendation on consumer behavior, as shown in Figure 1.

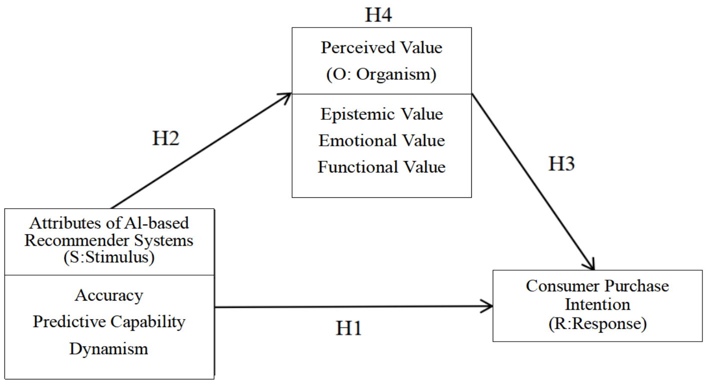


**Figure 1** Research Framework

## 4. Materials and Methods

4.1 Research Instruments

This study uses a questionnaire survey to measure each variable. The questionnaire is modified based on mature scales and the AI recommendation context. It is divided into two parts. The first part collects information such as gender, age, and platform use for descriptive statistics. The second part measures the core variables, including AI-based recommender system attributes, perceived value, and purchase intention. All items use a five-point Likert scale, where 1 = strongly disagree and 5 = strongly agree.

The AI recommendation attribute scale refers to existing research and is adjusted for this specific context. Accuracy refers to the perceived accuracy dimension of the ResQue model proposed by Pu, Chen, and Hu (2011). Predictive capability is based on the studies of Covington, Adams, and Sargin (2016) and He et al. (2017). Dynamism is based on the sequence modeling research of Hidasi et al. (2015) and the user evaluation method of Knijnenburg and Willemsen (2015). Technical expressions are rewritten into perception-based statements that are easier for users to understand. Perceived value, as an overall psychological evaluation variable, is based on Zeithaml's (1988) "get-give" trade-off and Sweeney and Soutar's (2001) PERVAL scale, and is revised with reference to Li and Karahanna (2015). The purchase intention scale is based on Dodds, Monroe, and Grewal (1991).

4.2 Sample

This study collects primary data through a questionnaire survey. It selects respondents with experience using AI recommendation and adopts purposive sampling and convenience sampling. Screening questions are used to identify valid respondents. The questionnaire is distributed anonymously. It is adapted from mature scales in combination with the AI recommendation context and uses a five-point Likert scale. A total of 451 questionnaires were distributed. After incomplete, patterned, and duplicate responses were removed, 400 valid samples were obtained, with an effective rate of 88.7%. This meets the requirements of empirical research. In the sample, women account for 54.75% and men account for 45.25%, showing a relatively balanced gender distribution. Regarding age, respondents aged 18-25 and 26-35 each account for 37.50%, together accounting for 75%. These groups are the main users of e-commerce , with long online usage time and fast acceptance of new technology. Regarding education, respondents with a bachelor's degree or above account for 64%, indicating a relatively high education level. Regarding usage time, respondents who use platforms for 30 minutes to 2 hours per day account for 69.25%. This indicates that most respondents have relatively long continuous usage experience and can evaluate recommender systems based on actual feelings. Overall, the sample has good representativeness and reliability.

## 5. Results and Discussion

To ensure internal consistency and stability of the measurement instruments, this study conducts reliability tests on three scales. Cronbach's alpha coefficient is used to evaluate the degree of homogeneity among items in each dimension. It is generally believed that an alpha value greater than 0.7 indicates an acceptable level of reliability. The test results are shown in Table 1. The AI-based recommender system scale contains 15 items, with an alpha value of 0.772, which is greater than 0.7. The perceived value scale contains 12 items, with an alpha value of 0.866, which is higher than 0.8. The consumer purchase intention scale contains 4 items, with an alpha value of 0.855, which also exceeds 0.8. All three scales show good internal consistency. This indicates that the measurement results of each scale are reliable and can be used for subsequent empirical analysis.

**Table 1** Reliability Analysis Results of Each Dimension

| Dimension | | Number of Items | Cronbach's α |
|---|---|---|---|
| AI-based recommender system | Accuracy | 5 | 0.772 |
| | Predictive capability | 5 | |
| | Dynamism | 5 | |
| Perceived value | Functional value | 4 | 0.866 |
| | Emotional value | 4 | |
| | Epistemic value | 4 | |
| Consumer purchase intention | | 4 | 0.855 |

To test the structural validity of the scales, that is, whether the measurement items accurately reflect the theoretical constructs, this study conducts exploratory factor analysis (EFA). The Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity are used to judge whether the data are suitable for factor extraction. A KMO value closer to 1 indicates that variables share more common factors, and a value greater than 0.7 is usually considered acceptable. Bartlett's test should be significant ($p < 0.05$). The results are shown in Table 2. For the AI-based recommender system scale, KMO = 0.890 and Bartlett's chi-square value

= 3756.839 ($p < 0.001$). For the perceived value scale, KMO = 0.871 and chi-square value = 2525.738 ($p < 0.001$). For the purchase intention scale, KMO = 0.824 and chi-square value = 675.619 ($p < 0.001$). The KMO values of all three scales are greater than 0.8, indicating that the variables share strong common factors and are highly suitable for factor analysis. The p values of Bartlett's test of sphericity are all less than 0.001, rejecting the null hypothesis that the variables are mutually independent. This shows that common variation exists in the correlation matrix. The common factors extracted by exploratory factor analysis are consistent with the theoretical dimensions, and the factor loadings of each item are reasonable. This proves that all three scales have good structural validity.

**Table 2** Summary of KMO and Bartlett's Test Results for Each Dimension

| Variable | KMO Value | Bartlett's Test Chi-Square Value |
|---|---|---|
| AI-based recommender system | 0.890 | $\chi^2$=3756.839, $p<0.001$ |
| Perceived value | 0.871 | $\chi^2$=2525.738, $p<0.001$ |
| Consumer purchase intention | 0.824 | $\chi^2$=675.619, $p<0.001$ |

After completing the reliability and validity tests of all scales and confirming their measurement reliability and structural validity, this paper further conducts Pearson correlation analysis. This analysis tests the linear relationships among the core variables, excludes the interference of multicollinearity, and provides a statistical basis for subsequent regression analysis and mediating effect testing.

As shown in Table 3, all variables are significantly and positively correlated at the 0.001 level. Among them, the correlation coefficient between AI-based recommender systems and consumer purchase intention is 0.568, which is a medium-to-high correlation. This indicates that the stronger the accuracy, predictive capability, and dynamism of recommender systems are, the more they can stimulate purchase desire by saving information search time and improving shopping efficiency. The correlation coefficient between perceived value and purchase intention is 0.551, confirming the core logic of "value-driven behavior" in consumer behavior studies. The correlation coefficient between AI-based recommender systems and perceived value reaches 0.724, indicating that technical attributes mainly affect purchase behavior by influencing users' subjective feelings. This provides preliminary evidence for mediating effect analysis. The data in Table 3 show that all correlation coefficients are less than 0.9, meaning that there is no serious multicollinearity. The variables have good discriminant characteristics, and the directions of correlation are fully consistent with the research expectations. This verifies the rationality of the theoretical framework of "technical attributes → perceived value → behavioral intention" and lays a solid foundation for subsequent empirical testing.

**Table 3** Correlation Analysis

| Variable | 1 | 2 | 3 |
|---|---|---|---|
| Consumer purchase intention | 1 | | |
| AI-based recommender system | 0.568** | 1 | |
| Perceived value | 0.551** | 0.724** | 1 |

Note: **p<0.001,Significant at the 0.01 level, two-tailed.

After completing Pearson correlation analysis and verifying significant positive correlations among the core variables, this paper further adopts multiple linear regression analysis. The analysis tests, in order, the direct effect of AI-based recommender system attributes on purchase intention, the effect of perceived value on purchase intention, and the effect of AI recommendation attributes on perceived value. Regression analysis can quantify the strength of relationships among variables and control for the influence of demographic and other confounding variables. It also provides the core empirical basis for subsequent mediating effect testing.

The Effect of AI-Based Recommender System Attributes on Consumer Purchase Intention

The regression results in Table 4 show that after control variables such as gender, age, education, and usage time are included, AI-based recommender systems have a significant positive effect on consumer purchase intention.The standardized coefficients (β) for Accuracy, Predictive capability, and Dynamism were 0.385, 0.305, and 0.318, respectively, and all coefficients were statistically significant ($p < 0.001$). The t value were 9.273, 7.328, and 7.697, respectively, indicating that this effect is significant and has strong explanatory power. From the perspective of the action mechanism, AI-based recommender systems, as exogenous technological stimuli, help consumers obtain needed product information in a short time by improving the degree of information matching. They reduce decision-making costs and strengthen decision confidence. At the same time, their predictive capability can anticipate users' potential needs, making recommendations more targeted and further increasing purchase desire. The overall model fit is good. $R^2$ is 0.335 and adjusted $R^2$ is 0.323. The F value is 28.203 and reaches statistical significance. None of the control variables shows a significant effect, indicating that AI-based recommender systems have a general effect on purchase intention across different groups. The Variance Inflation Factor (VIF) values are all close to 1, meaning that there is no serious multicollinearity. The Durbin–Watson statistic is 1.929, indicating that the residuals show no obvious autocorrelation. Overall, improving the accuracy, dynamism, and predictive capability of recommender systems can effectively increase consumer purchase intention. This has important practical significance for e-commerce platforms in optimizing recommendation strategies.

**Table 4** Regression Analysis of AI-Based Recommender System Attributes on Consumer Purchase Intention

| Variable | | Model 1 | | |
|---|---|---|---|---|
| | | β | T | VIF |
| AI-based recommender system | Accuracy | 0.385 | 9.273* | 1.017 |
| | Predictive capability | 0.305 | 7.328* | 1.018 |
| | Dynamism | 0.318 | 7.697* | 1.006 |
| Control | Gender | -0.036 | -0.867 | 1.015 |
| | Age | -0.061 | -1.466 | 1.014 |
| | Education | -0.056 | -1.357 | 1.015 |
| | Usage time | -0.004 | -0.096 | 1.017 |
| $R^2$ | | | 0.335 | |
| Adj $R^2$ | | | 0.323 | |
| F | | | 28.203 | |
| D-W | | | 1.929 | |

Note: *p<0.001

The Effect of Perceived Value on Consumer Purchase Intention

As shown in Table 5, after gender, age, education, and usage time are controlled, perceived value has a significant positive effect on consumer purchase intention (standardized coefficients $\beta = 0.551$, $p < 0.001$). The t value is 13.131, which verifies the core logic of "value-driven behavior" in consumer behavior studies. In terms of theoretical meaning, perceived value is the overall subjective judgment formed by consumers based on "what is received and what is given." In AI recommendation contexts, perceived value includes three dimensions: functional value, emotional value, and epistemic value. Functional value is reflected in the usefulness and efficiency of recommendations. Emotional value comes from the pleasant experience of being understood and satisfied. Epistemic value comes from new discoveries and cognitive expansion brought by the system. The model has an $R^2$ of 0.308 and an adjusted $R^2$ of 0.300. The F value is 35.050 and is statistically significant, indicating good overall model fit. None of the control variables reaches statistical significance, showing that the effect of perceived value on purchase intention is independent and stable. The VIF value is close to 1, indicating no multicollinearity problem. The Durbin–Watson statistic is 2.017, showing good residual independence. It should be emphasized that perceived value is not only an independent influencing factor, but also a "converter" that links technological systems and consumer behavior. It can transform objective technological capability into subjective psychological experience. This provides important theoretical and empirical support for subsequent mediating effect testing.

**Table 5** Regression Analysis of Perceived Value on Consumer Purchase Intention

| Variable | | Model 2 | | |
|---|---|---|---|---|
| | | β | T | VIF |
| Perceived value | | 0.551 | 13.131* | 1.001 |
| Control | Gender | -0.003 | -0.069 | 1.011 |
| | Age | -0.034 | -0.800 | 1.010 |
| | Education | -0.047 | -1.106 | 1.009 |
| | Usage time | 0.017 | 0.414 | 1.010 |
| $R^2$ | | | 0.308 | |

| | |
|---|---|
| Adj $R^2$ | 0.300 |
| F | 35.050 |
| D-W | 2.017 |

Note: *p<0.001

The Effect of AI-Based Recommender System Attributes on Perceived Value

As shown in Table 6, after control variables are included, AI-based recommender system attributes have a very strong positive effect on perceived value.The standardized coefficients (β) for Accuracy, Predictive capability, and Dynamism were 0.447, 0.451, and 0.382, respectively, and all coefficients were statistically significant ($p < 0.001$). The t value were 12.803, 12.895, and 10.982, respectively, indicating that technical attributes are the core driving factor in the formation of consumers' perceived value. The specific paths are as follows: accuracy directly enhances functional value by improving the fit between recommended content and user needs; dynamism improves users' perception of system intelligence by responding in real time to changes in user interests, thereby increasing epistemic value; predictive capability identifies potential needs, creates a sense of trust and being understood among users, and enriches functional and emotional experience at the same time. The model has strong explanatory power. $R^2$ is 0.529 and adjusted $R^2$ is 0.521, meaning that the model explains more than half of the variation in perceived value, which is a relatively high level in behavioral science research. The F value is 63.003 and is highly significant, showing excellent overall model fit. None of the control variables shows a significant effect, indicating that the effect of technical attributes on perceived value is not influenced by demographic characteristics. The VIF value is close to 1, indicating no multicollinearity problem. The Durbin–Watson statistic is 2.048, showing good residual independence. The results of this section clarify the prerequisite for a mediating effect, namely that AI recommendation attributes can significantly and positively influence perceived value. This provides key support for verifying the complete transmission mechanism of "AI recommendation attributes → perceived value → purchase intention."

**Table 6** Regression Analysis of AI-Based Recommender System Attributes on Perceived Value

| Variable | | Model 3 | | |
|---|---|---|---|---|
| | | β | T | VIF |
| AI-based recommender system | Accuracy | 0.447 | 12.803* | 1.017 |
| | Predictive capability | 0.451 | 12.895* | 1.018 |
| | Dynamism | 0.382 | 10.982* | 1.006 |
| Control | Gender | -0.048 | -1.366 | 1.015 |
| | Age | -0.044 | -1.191 | 1.014 |
| | Education | -0.011 | -0.225 | 1.015 |
| | Usage time | -0.018 | -0.488 | 1.017 |
| $R^2$ | | | 0.529 | |
| Adj $R^2$ | | | 0.521 | |
| F | | | 63.003 | |
| D-W | | | 2.048 | |

Note: *p<0.001

Mediating Effect Test

To clarify the transmission role of perceived value between AI-based recommender systems and consumer purchase intention, this study uses the PROCESS macro combined with the bootstrapping method to test the significance of the mediating effect. The results show that perceived value plays a significant partial mediating role. The indirect effect value is 0.3341, and the 95% confidence interval is [0.2000, 0.4704], which does not include zero and is statistically significant. At the same time, the direct effect of AI-based recommender systems on purchase intention remains significant (0.5584). This indicates that AI-based recommender systems influence purchase intention through two paths. The first path directly stimulates purchase desire by improving decision-making convenience. The second path indirectly promotes purchase by improving consumers' functional, emotional, and epistemic value. This result reveals the action mechanism of "technical attributes - psychological cognition - behavioral outcomes." It provides empirical support for e-commerce platforms to balance algorithm optimization with user experience and to improve conversion and user stickiness.

**Table 7** Mediating Effect Test

| | Type | Coefficient | Standard Error | 95% Confidence Interval Upper Limit | Lower Limit |
|---|---|---|---|---|---|
| Mediating Effect | Direct Effect | 0.5584 | 0.911 | 0.3793 | 0.7374 |
| | Indirect Effect | 0.3341 | 0.0434 | 0.2000 | 0.4704 |

Based on the above research and a comprehensive review of relevant literature, the proposed hypotheses were empirically tested. The results show that H1 to H4 are all supported and valid.

**Table 8** Summary of Hypothesis Testing Results

| | Hypothesis | Result |
|---|---|---|
| H1 | AI-based recommender system attributes have a significant positive effect on consumer purchase intention | Accept |
| H2 | AI-based recommender system attributes have a significant positive effect on perceived value | Accept |
| H3 | Perceived value has a significant positive effect on consumer purchase intention | Accept |
| H4 | Consumers' perceived value plays a mediating role between AI-based recommender system attributes and purchase intention | Accept |

## 6. Conclusion

This paper takes AI-based recommender systems as the research background and is based on the theoretical framework of "AI-based recommender system attributes—perceived value—consumer purchase intention." Through questionnaire survey and empirical analysis, this study tests the research hypotheses and reaches the following core conclusions.

1) The predictive capability, accuracy, and dynamism of AI-based recommender systems all have significant positive effects on consumer purchase intention. Recommender systems have been upgraded from simple information assistance tools to key factors that influence consumer decision-making. Predictive capability can identify users' potential needs in advance. Accuracy can improve the match between content and needs. Dynamism can respond to changes in user interests in real time. These three attributes form a complete technical capability system from the dimensions of "prediction—matching—adjustment" and jointly drive the improvement of consumers' purchase desire.

2) The core attributes of AI-based recommender systems have a significant positive effect on consumers' perceived value. Consumers' perception of algorithmic technology is not based on technical principles, but comes from usage experience. Accuracy and predictive capability bring functional value to users by saving information search time. The sense of surprise and the feeling of being understood brought by personalized recommendations form emotional value. Dynamically updated and diverse content expands users' cognitive boundaries and creates epistemic value. This shows that technological advantages must be transformed into value that users can perceive before they can truly play a role.

3) Perceived value is the core factor driving consumer purchase intention and conforms to the consumer behavior logic of "value guiding behavior." When consumers obtain relatively high functional, emotional, and epistemic value while using recommender systems, their satisfaction with the platform increases significantly and then turns into stronger purchase intention.

4) Perceived value plays a significant partial mediating role between AI-based recommender system attributes and consumer purchase intention. The bootstrapping test results show that the indirect effect is significant and the confidence interval does not include 0. This indicates that AI-based recommender systems do not simply act directly on consumer behavior. Instead, they influence consumer behavior through the transmission path of "technical attributes—perceived value—purchase intention."

Overall, from the two dimensions of technical capability and user experience, this paper systematically reveals the internal mechanism through which AI-based recommendation influences consumer purchase decisions. It enriches academic research in the fields of intelligent recommendation and consumer behavior, and also provides empirical support for e-commerce platforms to optimize recommendation algorithms, improve user experience, and increase conversion efficiency.

## 7. Limitations and Future Research Directions

Although this study has achieved certain results at the theoretical and empirical levels, it still has many limitations, which should be further improved and expanded in future research.

1) Regarding sample selection, this study only collects data through questionnaires. The sample source is relatively single, and the coverage of regions and populations is insufficient. Therefore, the generalizability of the research results is limited. Future research can expand the sample size, include respondents from different regions, cultural backgrounds, and age groups, and improve the general applicability of the conclusions.

2) Regarding model construction, this study only verifies the mediating effect of perceived value and does not introduce moderating variables such as users' technology acceptance, trust level, and platform type. Future research can add moderating variables and explore the boundary conditions of the model.

3) Regarding research methods, this study uses cross-sectional data and cannot reflect dynamic changes in user behavior over time. Future research can use panel data or experimental methods to analyze the long-term influence of AI-based recommender systems on user behavior. It can also extend the research context to short videos, social networks, and other fields, so as to improve related research findings.

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