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AI Recommendations: Benefit or Burden for Customer Satisfaction? Value Preferences Emerge as a Decisive Factor on E-commerce Platforms

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KEYWORDS

AI recommendations; consumer satisfaction; moderating role; value preferences

ABSTRACT

This study develops and empirically tests a conditional process model to explore the impact of AI recommendations on consumer shopping satisfaction on e-commerce platforms. In addition, this study investigated the moderating effect of consumer value preferences on the relationship between AI recommendations and purchase satisfaction. The findings indicate that AI recommendations cause information cocoons and have a significant negative main effect. However, this negative effect is not uniform. Its impact is significantly moderated by customer value preferences. We further uncover a significant gender divide in these moderating pathways. This study offers actionable insights for e-commerce platforms on how to tailor their recommendation algorithms not just to user profiles, but to user shopping motives.

1. INTRODUCTION

Currently, most online purchasing platforms are using AI recommendation technology to suggest the most suitable products for customers, increasing the sales conversion rate. For example, Amazon uses AI to analyze users browsing and purchase histories, providing personalized product recommendations that increase the likelihood of customer satisfaction and sales. By collecting and analyzing users' behavioral data, preference information, and content features, AI recommendations can generate a personalized recommendation list using algorithms such as collaborative filtering, content-based recommendation, or deep learning (Venice et al., 2025). By following the platform guidance, consumers have the opportunity to come across the products they need and end their search earlier, which can result in significant savings in consumer search costs (Chaure et al., 2024; Leng, 2024; Zhang & Wang, 2025). That is, AI recommendations can profoundly influence online service provision(Lim & Kim, 2025).

Although AI recommendations have a positive effect on online sellers and contribute to the improvement of purchasing experiences (Zuiderveen Borgesius et al., 2016), they have raised concerns about their potential negative impacts on users, particularly in the form of information cocoon. (Yang et al., 2024). The so-called information cocoon, means that users are exposed to repetitive content. Recommendation algorithms are constantly reinforcing consumers' existing preferences, filtering out other categories of goods that may be of interest but are not being actively explored. It seems that consumers get a lot of AI recommendation information in line with their preferences(Chen et al., 2022; Zhang et al., 2025). In fact, a large amount of homogenized information that conforms to personal preferences can over-occupy consumers' attention and cognitive energy, resulting in a period of time in which they have no time for non-homogenized information. Ultimately, it is difficult for consumers to be exposed to a wider range of content and choices.

Consequently, an increasing body of research focuses on the negative consequences of AI recommendations, such as the filter bubble effect (Piao et al., 2023), which can lead to cognitive rigidity, user fatigue (Li et al., 2024), and even cognitive polarization on social media. Some studies argue that most users hold negative views towards the filter bubble effect and seek to mitigate it. This negative characterization, however, ignores the crucial premise that the ultimate utility of AI recommendations is not determined by the technology itself, but rather is subjectively constructed by users through their individual psychological needs.

Based on the above analysis, this study focuses on the idea that the utility of AI recommendations varies across users. Specifically, users' overall perception of AI personalization interacts with their individual psychological traits, shaping heterogeneous outcomes. To explore this, we developed and tested a moderated model to examine how consumer shopping value preferences—personalization and efficiency preferences—act as boundary conditions, influencing the relationship between AI personalization perception and online shopping satisfaction. In light of this,, this study attempts to address the following two key issues.

RQ1: How does individual value preferences moderate the impact of AI recommendations on shopping satisfaction?

RQ2: What are the distinct mechanisms through different value preferences shape the consumer's response to AI personalization?

By addressing these two issues, this study contributes to AI-driven recommendations by considering the match between humans and technology. First, while some scholars have noted the issue of information cocoon caused by AI recommendations, little is known about the impact of consumer psychological effects on online shopping satisfaction. Therefore, this study explores the key boundary condition of consumer value preferences, uncovering the black box of personalization heterogeneity effects. Second, by developing a robust survey and employing moderated regression analysis, we test hypotheses on a sample of online shoppers. The findings not only contribute to theoretical discussions on human-computer interaction and human-environment alignment in digital contexts but also provide clear, evidence-based guidance for practitioners on how to design and implement adaptive personalization strategies.

This paper is divided into five sections. The first section is introductory, which presents the background, the key issues to be addressed, and the innovations. The second section is the literature review, which describes the relevant aspects of AI recommendations and personal decision-making styles. The third section presents the theory and research hypotheses. Section four describes the data collection process. Section five presents the empirical analysis, including the test of the moderating effect of AI recommendation on the relationship between consumer preference. The sixth section concludes the paper.

2. LITERATURE REVIEW

2.1. AI recommendation

The adoption of AI-powered recommendation technologies by online platforms has become a prevalent strategy for enhancing user experience. Fundamentally, these systems perform an in-depth analysis of user data, such as search histories and transaction records, to align product attributes with the user profiles. This process facilitates the recommendation of items that are both highly relevant and tailored to individual preferences(Yoon & Lee, 2021). The adoption of AI technology creates value in multiple dimensions. From a consumer cognitive perspective, AI recommendations address the challenge of information overload, wherein users struggle to make effective choices. By presenting highly relevant products that reflect customer needs, these systems save users' cognitive effort and provide significant utilitarian value (Chang & Park, 2024). From a technical standpoint, AI-powered personalization expands the size of the consumer's consideration set and deepens their engagement with each considered option(Li et al., 2022; Yin et al., 2025). Consequently, from a business performance perspective, providing personalized recommendations has been shown to have a substantial impact on user satisfaction and loyalty. This, in turn, boosts click-through intentions, enhances purchase propensity, and ultimately generates greater sales revenue (Yin et al., 2025).

Notwithstanding the benefits, by shaping the flow of information, AI recommendations can also lead to unintended consequences for the consumer's online experience, with the information cocoon being the most notable consequence. The recursive dynamic between user activity and algorithmic curation can foster a state of informational homogeny(Han et al., 2022), which proves detrimental to consumers' online shopping satisfaction. This engenders a fundamental trade-off: short-term relevance is achieved at the expense of long-term immersion in an insular, algorithmically-defined information sphere. Such enclosure reinforces filter bubbles and amplifies ideological fragmentation among users (Flaxman et al., 2016; Min et al., 2019). This technologically shaped filter bubble or information cocoon is the core manifestation of the inherent paradox of AI recommendations.

Despite recognizing the dual effects of AI recommendations, prior research has predominantly treated consumers as monolithic entities, neglecting the heterogeneity of their shopping motivations. This oversight highlights the critical need to investigate the boundary conditions that shape the net impact of this double-edged sword.

2.2 Consumer value preferences

Consumers have two different motivations when shopping online: utilitarianism and hedonism (Bai et al., 2024; Ozen & Kodaz, 2012). Hair et al. (2017)argue that utilitarian motivation is a shopping approach focused on achieving effective goals and outcomes(Silalahi et al., 2025). Therefore, consumers primarily engage in conscious, goal-directed search behavior, focusing mainly on information relevant to their objectives. The satisfaction of hedonic consumers depends on whether their goals are achieved or the task is effectively completed(Babin et al., 1994). Therefore, when shopping online, they engage in highly purposeful searches, preferring clear product information and parameter comparisons, aiming to minimize search time and cognitive costs. In the cognition of hedonic consumers, AI recommendations serve as a tool to achieve online shopping goals, and they are more likely to accept personalized product recommendations that directly meet their specific needs(Yan et al., 2025). In contrast, hedonism focuses on users' personal desires for entertainment and emotional motivation (Yang & Lee, 2010; Yuan et al., 2022). Hedonic consumers make purchases not only for the practical value of the product but also to gain satisfaction during the shopping process(Sen et al., 2025). More specifically, if the retail environment can offer consumers fantasy fulfillment, perceived freedom, enhanced stimulation, and positive emotions (e.g., designer accessories, concerts), it can provide significant hedonic shopping value (Alzayat & Lee, 2021). Therefore, hedonistic consumers tend to engage in less directed, intentional, and focused exploratory search behavior when browsing information on e-commerce platforms(Wu et al., 2015). They seek pleasurable emotional experiences, discover surprises, satisfy their curiosity, and find unique products that express their personality. In such cases, AI might reduce the opportunities to encounter diverse choices.

Overall, the effectiveness of AI recommendations may vary significantly depending on users' value preference. This variation highlights the possibility that users with different decision-making styles may respond differently to algorithmic filtering and personalized recommendation services in e-commerce environments. Therefore, consumers' value preferences are no longer merely a background variable but a key moderating variable that determines the direction and intensity of AI personalized recommendations, and it is necessary to consider them.

3. THEORIES AND HYPOTHESIS

3.1 Expectation confirmation theory

According to the expectation-confirmation theory (ECT) (Oliver & Desarbo, 1988), satisfaction, along with continued usage, is considered essential for building and maintaining a loyal consumer relationship (Hsiao et al., 2016; Oliver & Desarbo, 1988). Bhattacherjee (2001) posited that the effect of expectation-performance fit is captured within the constructs of confirmation and satisfaction. He thinks the expectation-confirmation theory comprises four main constructs, namely expectation–confirmation, perceived usefulness, satisfaction and user continuance intention (Rahi et al., 2021). The ECT claims that expectations, along with perceived expectation, lead to post-purchase satisfaction. If the relationship between expectations and confirmation is negative, it implies that when consumers' expectations are too high and the actual performance does not surpass these expectations, the level of confirmation decreases, thereby indirectly affecting consumer satisfaction.

This study employs the confirmation-satisfaction framework of Expectation-Confirmation Theory (ECT) to explore the impact of AI recommendations on consumer satisfaction. Additionally, it investigates the effect of shopping continuation intention under the moderating role of heterogeneous consumers. Confirmation is determined based on customers' assessment of perceived service performance vis-à-vis their original expectations (Fu et al., 2018). In this regard, a higher expectation will lead to a negative confirmation. The information cocoon induced by AI recommendations represents a low level of perceived performance. This low performance leads to negative confirmation in relation to the user's expectations, which directly results in a decline in satisfaction. Therefore, the following hypotheses are proposed:

H1: AI recommendation perception has a negative influence on consumer satisfactory.

3.2 Uses and gratifications theory and cognitive load theory

Uses and Gratifications Theory (UGT) suggests that users use media to fulfill specific needs. This theory recognizes that individuals are driven to select specific media based on their socio-psychological needs (Tran, 2021). According to the UGT, people make deliberate choices about the media they engage with, aiming to fulfill their personal needs and achieve their communication goals. Furthermore, UGT posits that consumers are aware of the motivational drivers that influence their media selection (Yadav et al., 2024). Uses and gratification theory explains how people with different goals use media to fulfill their needs (Kim et al., 2020; Smock et al., 2011). This suggests that different consumers make purchases on online platforms for different motivations. Prior research has shown that consumer purchasing behavior is influenced by value preferences(Sinkovics et al., 2010; Yasin, 2015).

On the one hand, Garg et al. (2023) argued that hedonistic consumers tend to search exhaustively for all possible options before choosing the best option, seeking to maximize their benefits (i.e., utility) (Leshem, 2012; Sivasubramaniyam et al., 2020). The choice processes involving information gathering and deliberation(Wan & Nakayama, 2025). Based on SPROTLES and KENDALL (1986), we define hedonistic consumers as the follower of novelty fashion consciousness. According to (Eun Park et al., 2010), novelty and fashion conscious consumers derive sensory satisfaction from new items. However, the information cocoon directly deprives consumers of the pleasure of exploration, sense of surprise, and opportunity for self-expression during the shopping process, which completely hinders the fulfillment of hedonic needs. According to UGT, when a medium fails to satisfy a user's core motivation to use it, the user's satisfaction will drop dramatically. Therefore, for consumers with hedonic as the core motivation, the negative impact of information cocooning is significantly amplified.

On the other hand, time pressure has been shown to influence the psychological orientation of utilitarian consumer(Vermeir & Van Kenhove, 2005). Maggioni et al. (2019)argue that efficiency-preferred consumers would improve shopping happiness through a more efficient shopping experience. In addition, according to the cognitive load theory, the total mental effort required in information processing is a key factor in assessing the efficiency of information processing and decision making(Wang et al., 2024). Individuals are often "cognitive misers" and prefer to avoid unnecessary cognitive effort (Fiske & Taylor, 2020). For example, some travelers are willing to use only those new routes where the length of travel time meets their minimum time for which they are willing to travel. Therefore, we can infer that consumers with efficiency preferences want to minimize their cognitive load during the shopping process. On e-commerce platforms, AI recommendations help users focus on specific categories by repeatedly recommending similar products, which reduces the cognitive load on users to sift through massive amounts of information, serving the goal of efficiency to a certain extent. This reduction in cognitive load is a gain for utilitarian consumers, which can offset the loss caused by the lack of variety. Users may also feel a bit bored, but they are more tolerant of this side effect as long as it helps them accomplish their shopping tasks successfully.

In this light, we formulate the following hypothesis:

H2: Hedonism reinforce the negative impact of AI recommendations on online shopping satisfaction.

H3: Utilitarianism undermines the negative impact of AI recommendations on online shopping satisfaction.

In summary, this study constructs a conditional process model rooted in ECT and UGT theories to explore how AI recommendations affect online shopping customer satisfaction (Fig.1). The model posits that consumers' value preferences play the role of moderating variables that determine how customers respond to AI recommendations through these pathways.

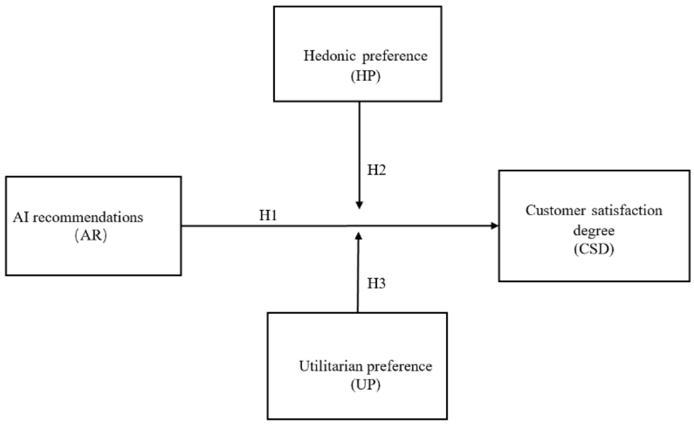

Fig.1 Conceptual Framework.

4. RESEARCH METHODS

4.1. Data collection

The data for this study were primarily collected through an online survey distributed via digital platforms. Online distribution was chosen because it is a more effective method of reaching users of e-commerce platforms, who are the target population for this study. To ensure that participants were indeed e-commerce users, a screening question was included in the survey: "Have you had any online shopping experience (e.g., Taobao, JD.com, Amazon, etc.) in the past three months?" This helped to exclude irrelevant respondents. Additionally, participants' perceptions of AI recommendations were measured using six questions, one of which was reverse scored to mitigate potential acquiescence bias. Respondents were asked to rank their agreement with each statement on a 5-point Likert scale ranging from "strongly disagree" to "strongly agree." Furthermore, drawing on the classic distinction between hedonic and utilitarian shopping motives (e.g., Childers et al. (2001)), we measured consumers' value preferences across two independent dimensions: hedonic and utilitarian preferences. Online shopping satisfaction focuses on post-purchase comprehensive evaluation, with the scale adapted from the classic literature on customer satisfaction and post-adoption behavior (e.g., (Kumar & Anjaly, 2017)). Finally, the items were specifically designed to capture consumers' overall emotional and cognitive evaluations of their shopping experiences after purchase. Respondents were asked to rank their agreement with this statement on a 5-point Likert scale ranging from "very dissatisfied" to "very satisfied."

To enhance the representativeness of the collected data, the survey was distributed to users with different occupations, income levels, and social status. The data collection period was from June 2025 to July 2025. A total of 250 questionnaires were distributed through an online survey platform. After excluding invalid responses (e.g., responses with unusually short durations), those containing uniform or patterned answers, those lacking substantive information, or those showing obvious random inputs, 204 valid responses were retained for analysis. This resulted in a valid response rate of 81.61%.

Table 1 Scales of measurement

Variable	Item		CITC	Factor Loading
AI recommendation	AR1	The products recommended to me by the shopping platform often seem to be from the same few categories.	0.684	0.749
	AR2	The platform repeatedly recommends items that are very similar to what I have recently searched for or viewed.	0.754	0.815
	AR3	Through the platform's recommendations, I find it difficult to discover novel product categories that I might like but wasn't previously aware of.	0.709	0.776
	AR4	I feel the platform filters my content too aggressively, screening out many potentially interesting items based on my browsing history	0.655	0.706
	AR5	While the products and content on the platform seem tailored to my tastes, their overall scope feels narrow and limited.	0.707	0.767
Utilitarian preference	UP1	My primary goal in online shopping is to get what I need as quickly as possible.	0.742	0.844
	UP2	I tend to choose platforms that make my shopping process as simple and direct as possible.	0.639	0.688
	UP3	I am unwilling to spend extra time browsing for items that I may or may not buy.	0.695	0.789
	UP4	Compared to the "fun of browsing," I care more about the "efficiency" of completing my shopping task.	0.666	0.731
Hedonic preference	HP1	For me, finding products that reflect my unique taste is very important when shopping.	0.660	0.733

	HP2	I genuinely enjoy the fun of exploring new brands and products when shopping online.	0.665	0.748
	HP3	I prefer shopping platforms that can offer me surprises and new discoveries	0.699	0.788
	HP4	I am more willing to shop on platforms that make me feel like "they really get me."	0.700	0.770
Customer satisfaction degree	CSD1	Overall, I am satisfied with my shopping experience using the platform's personalized recommendations.	0.822	0.854
	CSD2	This recommendation experience has met my expectations.	0.846	0.884
	CSD3	Using the recommendations on this platform has been a pleasant experience.	0.835	0.865
	CSD4	I believe that choosing to shop with the platform's recommendation feature was a wise decision.	0.834	0.864
	CSD5	I am willing to continue using the platform's personalized recommendation feature in the future.	0.840	0.875

4.2. Measures

The use of online shopping methods is influenced by individual characteristics (Kang, 2002; Lucas and Sherry, 2004; Valkenburg and Soeters, 2001). Accordingly, we included several demographic variables that have been used in prior research (Smock et al., 2011). At the end of the questionnaire, we asked respondents about their demographic factors, including gender, age, education level, monthly income, weekly online shopping frequency, and daily reliance on online shopping platforms. These variables were used as control variables, as shown in Table 2. Table 3 presents the descriptive statistics for all variables. This comprehensive coverage ensures that the data are both inclusive and representative, thereby supporting the robustness of the subsequent analyses.

To ensure content validity, the scale items in this study were adapted from the classic literature, and three doctoral students in related fields were invited to review the initial draft of the questionnaire.

Table 2 Descriptive Statistics of Survey Respondents

Variable	Category	Sample size	Percentage (%)
Gender	Male	99	0.49
	Female	105	0.51
Age	19-25	48	23.53

	26-30	78	38.24
	31-40	58	28.43
	41-50	13	6.37
	Above 51 years old	7	3.43
Education Background	High school or below	30	14.71
	Junior college	52	25.49
	University	95	46.57
	Graduate school	27	13.24
Monthly income level	Below 3000 CNY	27	13.24
	3001-5000 CNY	56	27.45
	5001-8000 CNY	80	39.22
	8001-15000 CNY	29	14.22
	More than 15001 CNY	12	5.88
Frequency of usage in a week	Less than once	26	12.75
	1-2 times	94	46.08
	3-5 times	66	32.35
	More than 5 times	18	8.82
Degree of dependence on online recommendation	1	20	9.8
	2	38	18.63
	3	64	31.37
	4	52	25.49
	5	30	14.71

Table 3Descriptive statistics of variables

Variable	Minimum	Maximum	Mean	Standard Deviation	Kurtosis	Skewness
AI recommendation	1.000	5.000	3.236	0.939	-0.55	-0.184
Hedonistic preference	1.000	5.000	3.263	0.956	-0.411	-0.336
Utilitarian preference	1.000	5.000	3.249	0.965	-0.45	-0.257
Customer satisfaction degree	1.000	5.000	3.193	1.047	-0.789	-0.204

5. EMPIRICAL RESULTS

5.1 Reliability and validity tests

To test the construct validity of the measurement tools used in this study, we employed confirmatory factor analysis (CFA). The analysis was conducted using AMOS 24.0 software. The CFA model included all core constructs in our study, namely AI information silos, hedonistic preferences, utilitarian preferences, and online shopping satisfaction.

Table 4 Model Fit Indices

Common Indicators	χ^2	df	χ^2/df	GFI	RMSEA	SRMR	CFI	NFI	AGFI
Evaluation Criteria	-	-	<3	>0.9	<0.10	<0.08	>0.9	>0.9	>0.9
Observed Values	153.063	129	1.187	0.926	0.03	0.039	0.989	0.935	0.987

The CFA results showed that the overall fit of the measurement model was found to be good (χ^2/df =1.187; CFI =0.989; RMSEA = 0.03; SRMR =0.039), and all the metrics met the acceptable criteria, which suggests that our measurement model has a good degree of fit to the sample data.

Table 5 Cronbach's α Coefficient and Test Results of Discriminant Validity

Variable	Cronbach's α	AVE	CR	AR	HP	UP	CSD
AR	0.874	0.583	0.875	0.763			
HP	0.848	0.585	0.849	0.256^{**}	0.765		
UP	0.845	0.578	0.845	0.309^{**}	0.260^{**}	0.760	
CSD	0.939	0.754	0.939	-0.518^{**}	0.371^{**}	0.050	0.869

Note: The diagonal values represent the square roots of the AVE for each construct.

As presented in Table 5, the measurement model demonstrates strong reliability and validity. All constructs' composite reliability (CR) and Cronbach's alpha values exceeded the 0.70 benchmark. Convergent validity was established, as the average variance extracted (AVE) for each construct was above the recommended 0.50 threshold. Furthermore, discriminant validity was supported, as the square root of each construct's AVE (the diagonal values) was greater than its correlation with any other construct. These results confirm the quality of our measurement.

5.2 Hypothesis testing

To verify the negative effect of AI recommendations on customer satisfaction, we conducted a regression analysis after controlling for consumer gender, age, educational attainment, monthly income, weekly platform usage frequency, and dependence on platform recommendations. The baseline regression results are shown in Table 6.

Table 6 Baseline test results

Variable	CSD	
	B(Coefficient)	95%CI
AI Recommendation	-0.747	-0.888 ~ -0.606
Gender	0.017	-0.219 ~ 0.253
Age	-0.001	-0.118 ~ 0.116
Education Level	0.002	-0.133 ~ 0.138
Monthly Income	-0.097	-0.208 ~ 0.014
Usage Frequency	-0.103	-0.248 ~ 0.043
Dependence	0.295	0.185 ~ 0.404
Constant	5.160	4.365 ~ 5.955
F-statistic	16.771	
Adjusted R^2	0.352	

As shown in Table 6, the effect of AI recommendation on customer satisfaction was -0.747, with a 95% confidence interval of [-0.888, -0.606], suggesting a significant negative effect, which indicates that AI recommendation counterintuitively reduces customer satisfaction.

Given that the overall effect of AI recommendations is negative, does this negative effect apply equally to everyone? Are there certain groups of people (e.g., efficiency-oriented individuals) who are immune to or even benefit from AI recommendations, while others (e.g., exploration-oriented individuals) are severely harmed by them. To investigate this, we now proceed to test the moderating role of consumer value preferences.

Table 7 Moderating effect test results

Variable	CSD (1)	CSD (2)
AR	-0.750^{**} (-12.453)	-0.786^{**} (-11.342)
AR*HP	-0.116^{*} (-2.081)	
HP	0.577** (9.095)	
AR*UP		0.250^{**} (4.014)
UP		0.191^{**} (3.007)
Controls	Control	Control
Constant	3.448^{**} (10.912)	2.632^{**} (7.373)
Observations	204	204
F-statistic	28.683	17.122
Adjusted R^2	0.551	0.417

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, t-values in parentheses.

According to the moderating effect test results in column (1) of Table 7, the interaction term between hedonistic preference and AI recommendations is significant at the 10% level. This indicates that hedonistic preference amplifies the negative effect of AI recommendation on customer satisfaction. Specifically, consumers with stronger preferences for personalization exhibit greater dissatisfaction when exposed to standardized AI recommendations. Hence, H2 is proven.

Conversely, as shown in Column (2) of Table 7, the interaction term between utilitarian preference and AI recommendations is significantly positive, demonstrating a buffering effect on the negative impact of AI recommendations on customer satisfaction. As established earlier, efficiency-oriented consumers value the time-saving benefits of AI recommendations, which facilitate streamlined decision-making by enabling swift identification of desired products. Hence, H3 is proven.

To further test the heterogeneity of the results, we conducted a complementary analysis by stratifying the sample by gender into male and female sub-samples. This approach assesses whether our empirical findings are consistent across demographic segments.

Table 8Heterogeneity analysis results of gender

Variable	CSD (1) Male	CSD (2) Female	CSD (3) Male	CSD (4) Female	CSD (5) Male	CSD (6) Female
AR	-0.827** (-7.371)	-0.714** (-7.298)	-0.879** (-9.518)	-0.688** (-8.411)	-0.855** (-7.810)	-0.752** (-8.113)
AR*HP			-0.101 (-1.217)	-0.160* (-2.110)		
HP			0.636** (7.220)	0.576** (6.232)		
AR*UP					0.178 (1.894)	0.350** (3.798)
UP					0.238* (2.571)	0.134 (1.475)
Controls	Control	Control	Control	Control	Control	Control
Observations	99	105	99	105	99	105
Constant	5.633** (9.884)	4.814** (8.310)	3.386** (8.963)	3.397** (7.215)	2.887** (6.036)	2.371** (4.697)
F-statistic	10.174	9.560	18.450	16.207	9.345	10.374
Adjusted R^2	0.36-	0.331	0.588	0.539	0.405	0.419

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1, t-values in parentheses.

As shown in columns (1)-(2) of Table 8, AI recommendations negatively impact consumer satisfaction in both male and female groups. However, the moderating effects differ across genders. Among males, efficiency demonstrates a significant moderating effect, whereas among females, maximization preference exhibits a more pronounced moderating effect. This divergence may be attributable to systematic differences in shopping motivations and information processing styles between genders, as widely documented in the consumer behavior literature (Kanwal et al., 2022; Smock et al., 2011; Zhang et al., 2014).

Specifically, the stronger moderating effect of utilitarian preference among the male sample aligns with the established agency-communion theory. Men often exhibit more agentic traits in consumption contexts, approaching shopping as a goal-oriented and task-focused activity. They prioritize functionality and speed (Doherty & Doherty, 2018). Consequently, when AI recommendations cater to their core need for efficiency, the system's value is more pronounced, thus more significantly moderating its overall effect on their satisfaction.

Conversely, female consumers tend to exhibit stronger communal traits, viewing shopping as an experiential, emotional, and social activity. They derive greater value from exploration, discovery and self-expression (Weigl, 2009). Therefore, their satisfaction is more sensitive to whether AI recommendations can deliver a diverse and engaging exploratory experience, which explains the stronger moderating effect of this preference within the female group.

This heterogeneity is not coincidental but is rooted in fundamental differences in consumption values. Men are more likely to appraise AI recommendations as an efficiency tool, whereas women are more likely to appraise them as an experience partner. This finding has important practical implications for platform operators seeking to tailor their algorithmic strategies to different user segments.

6. CONCLUSIONS AND IMPLICATIONS

6.1 Conclusions

This study examined the impact of AI recommendations on customer satisfaction within e-commerce platforms, highlighting the moderating role of value preferences. The conclusions of the study are as follows. First, the impact of information overload on customer satisfaction is negative, but this negative effect depends on differences in customer value preferences. Specifically, for consumers who highly value efficiency, the negative impact of AI recommendations is significantly mitigated because the technology aligns with their core need to complete shopping tasks quickly and accurately. Conversely, for consumers who prioritize personalization and exploration, this negative impact is further amplified because the information bubble directly conflicts with their hedonistic motivation. Second, the moderating effect of personalization preferences differs significantly between genders. Specifically, the moderating effect of efficiency preferences is more prominent among male consumers, while the moderating effect of personalization preferences is more pronounced among female consumers. This suggests that men are more likely to view AI recommendations as an efficiency tool for achieving goals, while women are more likely to view them as an exploratory partner for enriching the shopping experience.

6.2 Managerial implications

This study provides several managerial implications. First, give users some control over the algorithm. Since information silos are the main reason for declining satisfaction, platforms can design features that allow users to actively explore. For example, providing a surprise mode button or allowing users to manually adjust the weighting of diversity and relevance in recommendations can not only improve the user experience but also enhance users' sense of control and trust. Second, consider gender differences in refined operations. When conducting A/B testing or designing marketing campaigns, the platform can take gender factors into account. For example, the recommendation interface for male users can emphasize utilitarian values such as efficiency and time-saving, while the interface for female users can emphasize hedonistic and personalized elements such as discovery, trends, and exclusive tastes.

6.3 Limitations

This study also has some limitations. First, this study uses cross-sectional data, which cannot fully capture the dynamic evolution of user satisfaction. Future research could utilize longitudinal data or experimental methods to explore the long-term effects of information silos. Second, this study only considered two types of value preferences; future research could incorporate additional individual difference variables, such as consumption attitudes or innovation adoption rates. Finally, the sample in this study primarily comes from a specific cultural context; future research could conduct cross-cultural comparisons to test the generalizability of the study's conclusions.

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