International Journal of Management Science Research, Vol.9, Issue 5, (May) 2026
ISSN 2536-605X
DOI: 10.53469/ijomsr.2026.09(05).01

The Mechanism Through Which AI Algorithmic Recommendations Influence Users' Behavioral Intentions: A Comparative Analysis of Consumption and Public Health Service Contexts

Wei Zhu, Ping Ouyang*, Xiuting Mei

School of Economics and Management, Jiangxi Polytechnic University, Jiujiang 332005, Jiangxi, China
**Correspondence Author, ouyangping@jxpu.edu.cn*

Abstract: ***With the widespread application of AI algorithmic recommendations on digital platforms, their influence on users' behavioral decision-making has attracted increasing scholarly attention. Based on the stimulus–organism–response framework, the technology acceptance model, and trust theory, this study constructs a research model to examine how AI algorithmic recommendations affect users' behavioral intentions, and further conducts a comparative analysis between consumption and public health service contexts. Questionnaire data were collected from 312 valid respondents, and partial least squares structural equation modeling and multi-group analysis were employed for empirical testing. The results show that recommendation accuracy and recommendation transparency significantly enhance user trust, while recommendation reliability significantly strengthens perceived usefulness. Both user trust and perceived usefulness have significant positive effects on behavioral intention and play mediating roles between algorithmic recommendation characteristics and behavioral intention. Further analysis reveals that the consumption context relies more heavily on personalized recommendations and interest matching, whereas the public health service context depends more strongly on the professionalism and reliability of recommendation systems as well as trust mechanisms. This study enriches research on AI algorithmic recommendations from a context-comparative perspective and provides practical implications for optimizing recommendation mechanisms on digital platforms and promoting intelligent governance in public health services.***

Keywords: AI algorithmic recommendation; User behavioral intention; User trust; Perceived usefulness; Public health services; PLS-SEM.

1. INTRODUCTION

With the rapid development of artificial intelligence, big data, and the platform economy, algorithmic recommendation has become an important technological mechanism through which digital platforms connect users, information, products, and services. At present, e-commerce platforms, short-video platforms, social media platforms, as well as online medical and public health service platforms widely use AI algorithms to provide personalized recommendations of products, content, physicians, health information, and related services based on user profiles, browsing records, interaction behaviors, and contextual data. These recommendations continuously influence how users access information and make behavioral decisions (Konstan & Riedl, 2012; Xiao & Benbasat, 2007). Existing studies have shown that factors such as recommendation accuracy, recommendation transparency, recommendation reliability, and perceived user control can affect users' trust in platform-recommended content, perceived usefulness, and subsequent behavioral responses (Komiak & Benbasat, 2006; Xu & Chen, 2025). Meanwhile, with the development of explainable artificial intelligence, algorithmic transparency and explainability are regarded as important conditions for enhancing user trust, reducing perceived uncertainty, and promoting the acceptance of AI applications (Shin, 2021; Rosenbacke et al., 2024). In addition, in algorithmic recommendation environments, users may exhibit algorithm appreciation, but they may also develop algorithm aversion due to algorithmic errors and opacity (Logg et al., 2019; Dietvorst et al., 2015).

From the perspective of consumption contexts, algorithmic recommendation has been deeply embedded in the daily consumption processes of Generation Z users. As digital natives, Generation Z users show high engagement with short-video platforms, social media, content communities, and e-commerce platforms. Their consumption decisions are often jointly shaped by platform-recommended content, interest tags, influencer recommendations, and social interactions. Compared with traditional consumption decision-making, consumption behavior in algorithmic recommendation environments no longer relies entirely on users' active search, but gradually takes shape through the process of "platform push—interest stimulation—cognitive evaluation—behavioral conversion" (Zhu & Chang, 2016). Precisely matched recommended content can reduce users' information search costs, improve the visibility of products and services, and further enhance users' purchase intention and continued usage intention (Benbasat & Wang, 2005; Knijnenburg et al., 2012). However, while algorithmic recommendation improves platform efficiency, it may also give rise to problems such as information cocoons, privacy concerns, perceived algorithmic manipulation, and excessive consumption, thereby weakening users' trust in platform recommendation mechanisms (Zhang & Sundar, 2019).

From the perspective of public health service contexts, the application of AI algorithmic recommendation has stronger professional and risk-related attributes. Currently, online medical platforms, internet hospitals, health management apps, and public health service platforms are increasingly using algorithmic recommendation to provide users with health education content, physician resources, disease prevention information, and personalized health management suggestions. Unlike general consumption contexts, public health services involve disease prevention, health management, and medical decision support. Users are concerned not only with whether the recommended content meets their personal needs, but also with whether the recommendation source is professional, whether the recommendation process is reliable, and whether the recommendation results are explainable (Chew et al., 2022). Existing studies have indicated that users' acceptance of AI health services depends largely on their trust in recommendation systems and their perception of system professionalism (Kauttonen et al., 2025). Especially when health information involves professional barriers and potential risks, whether users adopt algorithm-recommended content often depends on their overall credibility judgment of the recommendation system, recommended information, and platform service capability (Qin, 2024; Zhang et al., 2014).

Existing research has examined the effects of algorithmic recommendation from the perspectives of consumer behavior, technology acceptance, intelligent recommendation, and online health information adoption. However, further research is still needed. First, most existing studies focus on a single context, such as e-commerce consumption or online medical services, while comparative analyses of the mechanisms through which algorithmic recommendation operates across different contexts remain relatively insufficient. Second, although prior studies have paid considerable attention to personalization, accuracy, and trust mechanisms in algorithmic recommendation, the differences in users' cognitive mechanisms between consumption contexts and public health service contexts have not been fully discussed. Third, as algorithmic recommendation gradually extends from commercial consumption platforms to the field of public health services, further research is needed on how platforms in different contexts should optimize recommendation mechanisms, enhance user trust, and improve algorithmic governance.

Based on this background, this study takes AI algorithmic recommendation as its research object and conducts a comparative analysis of consumption and public health service contexts. It constructs a research framework of "algorithmic recommendation characteristics—users' cognitive evaluation—behavioral intention" and focuses on examining the mechanisms through which recommendation accuracy, recommendation transparency, and recommendation reliability influence user trust, perceived usefulness, and behavioral intention. This study argues that algorithmic recommendation in consumption contexts places greater emphasis on interest matching, personalized experience, and content value, whereas algorithmic recommendation in public health service contexts depends more strongly on professional reliability, risk control, and trust construction. By comparing the common and different mechanisms through which algorithmic recommendation influences users' behavioral intentions in the two contexts, this study aims to provide theoretical references and practical implications for digital platforms to optimize recommendation services, improve user behavioral conversion, and promote the intelligent governance of public health services.

2. THEORETICAL FOUNDATIONS AND RESEARCH HYPOTHESES

2.1 Theoretical Foundations

2.1.1 S-O-R Theory

The stimulus–organism–response (S-O-R) theory was first proposed by Mehrabian and Russell. It suggests that individual behavior is formed as a behavioral outcome through internal psychological cognition and affective responses under the influence of external environmental stimuli (Mehrabian & Russell, 1974). In recent years, S-O-R theory has been widely applied in studies on digital platform user behavior, online consumption behavior, and intelligent recommendation systems to explain how external technological environments influence behavioral responses through users' cognitive and affective mechanisms (Zhao et al., 2020).

In the digital platform environment, AI algorithmic recommendation systems can provide users with personalized information recommendations through user data analysis, behavior prediction, and content filtering, thereby constituting an important external stimulus that influences user behavior. Existing studies have shown that the accuracy, transparency, and reliability of recommended content affect users' cognitive evaluations of platforms and recommended content, and further influence their behavioral decisions (Shin, 2020; Komiak & Benbasat, 2006). In the context of AI algorithmic recommendation, recommendation characteristics can be regarded as external stimuli, users' cognitive evaluations of the recommendation system, such as trust and perceived usefulness, belong to organism responses, while purchase intention, health information adoption intention, and continued usage intention represent behavioral responses. Especially when algorithms are deeply embedded in platform service processes, user behavior no longer relies entirely on active search, but is gradually shaped under the continuous influence of platform recommendation mechanisms. Therefore, S-O-R theory can effectively explain the internal mechanism through which AI algorithmic recommendation influences users' behavioral intentions.

In addition, users' cognitive focus on algorithmic recommendation may differ across contexts. In consumption contexts, users pay more attention to whether recommended content matches their interests, preferences, and consumption needs. In public health service contexts, however, because health information is highly professional and involves potential risks, users pay greater attention to the reliability, professionalism, and credibility of recommendation systems (Chew et al., 2022). Therefore, constructing a cross-context behavioral mechanism model of algorithmic recommendation based on S-O-R theory is theoretically reasonable.

2.1.2 Technology Acceptance Model

The technology acceptance model (TAM), proposed by Davis, argues that users' acceptance of technology mainly depends on perceived usefulness and perceived ease of use, among which perceived usefulness is an important factor influencing users' behavioral intentions (Davis, 1989). When users believe that a technology can improve task performance or meet their own needs, their intention to accept and continue using it will be significantly strengthened.

With the widespread application of AI recommendation technologies in platform services, perceived usefulness has gradually become an important variable for explaining users' acceptance of algorithms. Existing studies have suggested that when users believe algorithmic recommendations can improve information acquisition efficiency, reduce search costs, and enhance content matching, their reliance on recommendation systems and behavioral acceptance intention will significantly increase (Venkatesh et al., 2003; Konstan & Riedl, 2012). In consumption contexts, algorithmic recommendation helps users quickly discover products and content that match their interests and preferences. In public health service contexts, algorithmic recommendation can assist users in filtering health information, obtaining medical resources, and optimizing health decisions (Kauttonen et al., 2025).

At the same time, perceived usefulness is influenced not only by the quality of recommended content, but also by users' overall cognitive evaluation of the recommendation system. When users perceive the recommendation mechanism as more transparent, reliable, and trustworthy, they are more likely to develop a higher evaluation of perceived usefulness, which in turn strengthens their behavioral intention (Gefen et al., 2003). Therefore, this study regards perceived usefulness as an important cognitive variable through which AI algorithmic recommendation influences users' behavioral intentions.

2.1.3 Trust Theory

In algorithmic recommendation environments, users often find it difficult to directly judge the authenticity and effectiveness of recommended content. Therefore, trust becomes an important antecedent of user behavior. Trust theory suggests that when users develop a high level of trust in a platform, technological system, or recommended content, their perceived behavioral uncertainty decreases, making them more likely to form continued usage, purchase, or adoption behaviors (Gefen et al., 2003).

Compared with traditional information recommendation mechanisms, AI algorithmic recommendation is more strongly data-driven and characterized by a "black-box" nature, and users are usually unable to fully understand the recommendation logic and operating process. Therefore, whether the recommendation system is reliable, whether the recommendation results match users' needs, and whether the recommendation mechanism has a certain degree of transparency directly affect users' level of trust in the platform (Shin, 2021). Existing studies have shown that recommendation explanation mechanisms and the degree of personalization significantly influence users' trust in recommendation systems and their adoption intention (Wang & Benbasat, 2007; Komiak & Benbasat, 2006).

Trust is particularly important in public health service contexts, where health information involves individual health risks and medical decision-making. When users perceive the source of recommended information as reliable, the recommendation logic as reasonable, and the platform as professional, they are more likely to develop health information adoption intention and continued usage behavior (Qin, 2024; Rosenbacke et al., 2024). In addition, existing studies have indicated that trust not only directly affects users' behavioral intentions, but also further influences their evaluation of the perceived usefulness of technological systems. When users have greater trust in an algorithmic recommendation system, they tend to perceive the recommendation results as more valuable and practically helpful (Benbasat & Wang, 2005). Therefore, this study argues that trust plays a key mediating role in the process through which AI algorithmic recommendation influences users' behavioral intentions.

2.2 Research Model Development

Based on the S-O-R theory, the technology acceptance model, and trust theory, this study constructs a research model to examine how AI algorithmic recommendations influence users' behavioral intentions. Existing studies have shown that the personalization, transparency, and reliability of algorithmic recommendation systems affect users' cognitive evaluations of platform-recommended content and further influence users' behavioral responses (Komiak & Benbasat, 2006; Shin, 2021). Therefore, this study argues that algorithmic recommendation characteristics, including recommendation accuracy, recommendation transparency, and recommendation reliability, influence users' cognitive evaluations of recommendation systems, and further affect users' behavioral intentions through user trust and perceived usefulness.

Among these factors, recommendation accuracy mainly reflects the degree of matching between recommended content and users' interests and needs; recommendation transparency mainly reflects users' understanding of recommendation logic and recommendation criteria; and recommendation reliability reflects the authenticity, stability, and credibility of recommended content. Users' cognitive evaluations mainly include user trust and perceived usefulness, while behavioral outcomes are reflected in behavioral responses such as purchase intention, health information adoption intention, and continued usage intention (Davis, 1989; Gefen et al., 2003).

In addition, considering that consumption contexts and public health service contexts differ in terms of risk attributes, professional attributes, and users' decision-making objectives, this study further compares the differences in the influence mechanisms of algorithmic recommendation across different contexts. Consumption contexts place greater emphasis on interest matching and personalized experiences, whereas public health service contexts rely more heavily on the professionalism and credibility of recommendation systems (Chew et al., 2022; Kauttonen et al., 2025).

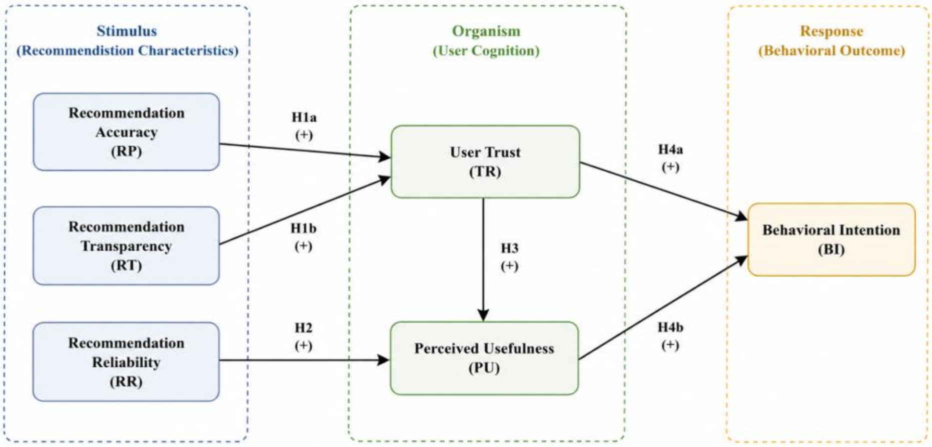

Figure 1: Research model

2.3 Research Hypotheses

The core objective of AI algorithmic recommendation is to achieve precise matching of content, products, and services through user data analysis and behavioral prediction. Existing studies have shown that recommendation accuracy can improve users' perceptions of content matching and their evaluation of platform capability, thereby enhancing users' trust in recommendation systems (Komiak & Benbasat, 2006). At the same time, recommendation transparency can reduce users' perceived uncertainty regarding the algorithmic "black box," enabling users to better understand recommendation logic and recommendation criteria, and further improving their evaluation of the credibility of recommendation systems (Shin, 2020; Wang & Benbasat, 2007). In addition, recommendation reliability reflects the authenticity, stability, and effectiveness of recommended content. When users perceive recommendation results as more reliable, they are more likely to regard the recommended content as having practical reference value and utility, thereby forming higher levels of perceived usefulness (Gefen et al., 2003; Xu & Chen, 2025). Therefore, this study argues that recommendation accuracy, recommendation transparency, and recommendation reliability, as important characteristics of AI algorithmic recommendation, significantly influence users' cognitive evaluations. Accordingly, the following hypotheses are proposed:

H1a: Recommendation accuracy positively influences user trust.
H1b: Recommendation transparency positively influences user trust.
H2: Recommendation reliability positively influences perceived usefulness.

In algorithmic recommendation environments, users' behavioral intentions are often not directly determined by technological characteristics, but are influenced by users' cognitive evaluation processes. According to the technology acceptance model and trust theory, when users develop higher trust in algorithmic recommendation systems, they are more likely to perceive recommended content as valuable and practically helpful, thereby enhancing perceived usefulness (Gefen et al., 2003). Meanwhile, user trust can reduce users' perceived uncertainty regarding recommendation results and strengthen their intention to accept recommended content and continue using the platform (Benbasat & Wang, 2005). Perceived usefulness further influences whether users are willing to adopt recommended content, use platform services, and form continuous behavioral responses (Davis, 1989; Venkatesh et al., 2003). Therefore, user trust and perceived usefulness not only directly influence users' behavioral intentions, but may also play mediating roles between algorithmic recommendation characteristics and behavioral intention. Accordingly, the following hypotheses are proposed:

H3: User trust positively influences perceived usefulness.
H4a: User trust positively influences users' behavioral intentions.
H4b: Perceived usefulness positively influences users' behavioral intentions.
H5a: User trust mediates the relationships between recommendation accuracy, recommendation transparency, and users' behavioral intentions.
H5b: Perceived usefulness mediates the relationship between recommendation reliability and users' behavioral intentions.
H5c: User trust and perceived usefulness play sequential mediating roles between algorithmic recommendation characteristics and users' behavioral intentions.

Users' cognitive focus on algorithmic recommendation differs across contexts. In consumption contexts, users are more concerned with whether recommended content matches their interests, preferences, and consumption needs, and algorithmic recommendation places greater emphasis on personalized experiences and content matching (Zhu & Chang, 2016). In public health service contexts, however, because health information involves strong professional attributes and potential risks, users pay greater attention to the reliability, professionalism, and credibility of recommendation systems (Qin, 2024; Rosenbacke et al., 2024). Therefore, the mechanisms through which AI algorithmic recommendation influences users' behavioral intentions may differ between consumption contexts and public health service contexts. Accordingly, the following hypothesis is proposed:

H6: The mechanisms through which AI algorithmic recommendation influences users' behavioral intentions differ between consumption contexts and public health service contexts.

3. RESEARCH METHODOLOGY

3.1 Research Model and Variable Design

Based on the S-O-R theory, the technology acceptance model, and trust theory, this study constructs a research model of “AI algorithmic recommendation characteristics—users’ cognitive evaluation—behavioral intention.” Among these variables, AI algorithmic recommendation characteristics include recommendation accuracy, recommendation transparency, and recommendation reliability; users’ cognitive evaluations include user trust and perceived usefulness; and the behavioral outcome is mainly reflected in users’ behavioral intentions.

Considering the characteristics of both consumption contexts and public health service contexts, this study defines users’ behavioral intention as users’ tendency to accept, adopt, and continuously use platform-recommended content. In consumption contexts, behavioral intention is mainly reflected in purchase intention, continued browsing intention, and recommendation acceptance intention. In public health service contexts, it is mainly reflected in health information adoption intention, public health service usage intention, and continued usage intention.

To ensure the scientific rigor and reliability of the measurement content, the measurement items for all variables were mainly adapted from established scales in previous domestic and international studies and were appropriately revised to fit the context of AI algorithmic recommendation. Specifically, recommendation accuracy mainly measures the degree of matching between recommended content and users’ interests and needs; recommendation transparency mainly measures users’ understanding of recommendation logic and recommendation criteria; recommendation reliability mainly measures the authenticity and credibility of recommended content; user trust mainly measures users’ overall trust in the recommendation system and platform; perceived usefulness mainly measures the extent to which users believe algorithmic recommendation can improve information acquisition efficiency and satisfy their personal needs; and behavioral intention mainly measures users’ tendency to accept and continuously use platform recommendation services. All measurement items in this study were assessed using a five-point Likert scale, where 1 indicates “strongly disagree” and 5 indicates “strongly agree.”

3.2 Questionnaire Design and Data Collection

This study adopted a questionnaire survey method to collect research data. The questionnaire mainly consisted of three parts. The first part collected respondents’ demographic information, including gender, age, educational level, and platform usage frequency. The second part focused on respondents’ experiences with AI algorithmic recommendation, including commonly used platform types, platform usage contexts, and user experiences with algorithmic recommendation. The third part contained the measurement items for the core variables, including recommendation accuracy, recommendation transparency, recommendation reliability, user trust, perceived usefulness, and behavioral intention.

Considering that this study mainly compares the differences in the influence mechanisms of AI algorithmic recommendation between consumption contexts and public health service contexts, scenario identification items were specifically included in the questionnaire. Based on respondents’ primary platform usage and usage purposes, the samples were divided into a consumption-context group and a public health service-context group. The consumption context mainly included consumption-oriented and content recommendation platforms such as Xiaohongshu, Douyin, Taobao, and JD.com, whereas the public health service context mainly included digital health service platforms such as Haodf.com, internet hospitals, health management apps, and WeChat health services.

The formal survey was mainly distributed online through the Wenjuanxing platform, combined with social media sharing and snowball sampling for data collection. The survey respondents mainly consisted of users with experience using AI algorithmic recommendation platforms. To improve questionnaire quality, the collected questionnaires were screened, and invalid responses with excessively short completion times, obvious response regularity, or logical inconsistencies were removed. The remaining valid samples were used for subsequent data analysis.

3.3 Variable Measurement

The variables examined in this study mainly include recommendation accuracy, recommendation transparency, recommendation reliability, user trust, perceived usefulness, and behavioral intention. To ensure the scientific rigor and reliability of the measurement scales, the measurement items for each variable were mainly adapted from established scales in previous domestic and international studies and appropriately revised to fit the context of AI algorithmic recommendation. Specifically, recommendation accuracy mainly measures the degree of matching between platform-recommended content and users' interests and needs; recommendation transparency mainly measures users' understanding of recommendation logic and recommendation criteria; recommendation reliability mainly reflects users' evaluations of the authenticity and credibility of recommended content; user trust mainly reflects users' overall trust in recommendation systems and platform services; perceived usefulness mainly measures the extent to which users believe algorithmic recommendation can improve information acquisition efficiency and satisfy their personal needs; and behavioral intention mainly reflects users' tendency to accept, adopt, and continuously use platform recommendation services.

To improve content validity, a small-scale pilot test was conducted before the formal survey, and several measurement items were revised and optimized based on the feedback received. All items were measured using a five-point Likert scale, where 1 indicates "strongly disagree" and 5 indicates "strongly agree." Table 1 presents the measurement items and reference sources for the main variables used in this study.

Table 1: Measurement Items of Variables

Variable	Code	Measurement Item	Reference Source
Recommendation Accuracy (RP)	RP1	The content recommended by the platform usually matches my interests and preferences.	Komiak & Benbasat (2006)
	RP2	The products, information, or services recommended by the platform can effectively meet my actual needs.	
	RP3	The platform can provide relatively personalized recommended content based on my usage behavior.	
Recommendation Transparency (RT)	RT1	I can generally understand why the platform recommends certain content to me.	Shin (2020/2021)
	RT2	The platform's recommendation mechanism can provide certain recommendation reasons or explanations.	
	RT3	The recommendation process of the platform is clear and understandable to a certain extent.	
Recommendation Reliability (RR)	RR1	I believe that the information recommended by the platform is generally reliable.	Gefen et al. (2003); Komiak & Benbasat (2006)
	RR2	The content recommended by the platform is usually highly credible.	
	RR3	The recommendation results provided by the platform can serve as a stable and reliable reference for my decision-making.	
User Trust (TR)	TR1	I trust the algorithmic recommendation content provided by the platform.	Gefen et al. (2003); Komiak & Benbasat (2006)
	TR2	I believe that the platform's algorithmic recommendation mechanism is trustworthy.	
	TR3	When using the platform's recommendation function, I generally feel confident about the recommendation results.	
Perceived Usefulness (PU)	PU1	Platform recommendations can help me obtain the information, products, or services I need more quickly.	Davis (1989)
	PU2	Platform recommendations improve my efficiency in obtaining information or making decisions.	
	PU3	Overall, the platform's recommendation function is helpful to me.	
Behavioral Intention (BI)	BI1	I am willing to continue using the platform's algorithmic recommendation function.	Davis (1989); Gefen et al. (2003); Komiak & Benbasat (2006)
	BI2	I am willing to further explore relevant information, products, or services based on the platform's recommendations.	
	BI3	I am still willing to accept personalized recommendations provided by the platform in the future.	

3.4 Data Analysis Methods

This study employed SPSS 26.0 and SmartPLS 4.0 for data analysis. First, SPSS 26.0 was used to conduct descriptive statistical analyses of the basic sample characteristics, including gender, age, educational level, platform usage frequency, and primary usage contexts, in order to understand the overall distribution of the sample.

Second, reliability and validity tests were conducted to verify the reliability and validity of the measurement model. Reliability was mainly evaluated using Cronbach's alpha coefficient and composite reliability (CR). When the values of Cronbach's alpha and CR exceed 0.70, the scale is considered to have good internal consistency. Convergent validity was mainly assessed through the average variance extracted (AVE). When the AVE value exceeds 0.50, the construct is considered to have satisfactory convergent validity. In addition, factor loadings and discriminant validity indicators were further used to examine the quality of the measurement model.

Third, this study employed partial least squares structural equation modeling (PLS-SEM) to test the research hypotheses. Compared with traditional covariance-based structural equation modeling, PLS-SEM is more suitable for prediction-oriented research and complex path relationship analysis, and it has relatively lower requirements regarding sample distribution. Therefore, it is appropriate for the research context of this study. The relationships among variables were mainly examined through path coefficients, t-values, and significance levels, and the mediating effects of user trust and perceived usefulness were further analyzed.

Finally, to compare the differences in the influence mechanisms of AI algorithmic recommendation across different contexts, this study employed multi-group analysis (MGA) to compare the consumption-context group and the public health service-context group. By comparing the significance differences in path coefficients, the similarities and differences in users' cognitive mechanisms and behavioral response mechanisms across different contexts were further examined.

4. EMPIRICAL RESULTS ANALYSIS

4.1 Sample Characteristics Analysis

A total of 356 questionnaires were collected in this study. After excluding invalid questionnaires with excessively short completion times, patterned responses, and logical inconsistencies, 312 valid questionnaires were retained, resulting in an effective response rate of 87.64%. Since this study mainly focuses on the influence of AI algorithmic recommendation on users' behavioral intentions, all respondents had prior experience using algorithmic recommendation platforms.

In terms of gender distribution, there were 142 male respondents, accounting for 45.5% of the sample, and 170 female respondents, accounting for 54.5%, indicating a relatively balanced gender structure. Regarding age distribution, respondents aged 18–25 accounted for the largest proportion, with 198 respondents representing 63.5% of the sample. Respondents aged 26–30 numbered 74, accounting for 23.7%, while respondents aged 31 and above numbered 40, accounting for 12.8%. Overall, the sample mainly consisted of Generation Z users, which is consistent with the target population of this study.

In terms of educational background, respondents with a bachelor's degree or above accounted for a relatively high proportion. Specifically, 186 respondents held a bachelor's degree, accounting for 59.6% of the sample; 54 respondents held a master's degree or above, accounting for 17.3%; and 72 respondents held a junior college degree, accounting for 23.1%. These results indicate that the respondents generally possessed relatively strong digital platform usage capabilities and information comprehension abilities.

Regarding platform usage frequency, 68.9% of respondents used algorithmic recommendation platforms more than three times per day, and 87.2% used such platforms more than five times per week, suggesting that the sample users had a high level of engagement with algorithmic recommendation platforms.

With respect to platform types, users in the consumption context mainly used platforms such as Xiaohongshu, Douyin, Taobao, and JD.com, among which the usage rates of Xiaohongshu and Douyin reached 61.5% and 74.4%, respectively. Users in the public health service context mainly used internet hospitals, health management apps, WeChat health services, and online consultation platforms, among which the usage rate of health education and online medical services reached 58.7%. Based on users' primary usage contexts, the final sample was divided into a consumption-context group (n = 178) and a public health service-context group (n = 134) for subsequent multi-group comparative analysis.

Table 2: Descriptive Statistics of Sample Characteristics

Variable	Category	Frequency	Percentage
Gender	Male	142	45.5%
	Female	170	54.5%
Age	18–25 years	198	63.5%
	26–30 years	74	23.7%
	31 years and above	40	12.8%
Context Type	Consumption Context	178	57.1%
	Public Health Service Context	134	42.9%

4.2 Measurement Model Assessment

4.2.1 Reliability Analysis

This study employed Cronbach's alpha coefficient and composite reliability (CR) to assess the internal consistency of the measurement scales. The results show that the Cronbach's alpha values of all constructs ranged from 0.812 to 0.914, all exceeding the recommended threshold of 0.70. The CR values ranged from 0.878 to 0.936, indicating that the measurement scales demonstrated satisfactory internal consistency and reliability.

Specifically, the Cronbach's alpha values for recommendation accuracy, recommendation transparency, recommendation reliability, user trust, perceived usefulness, and behavioral intention were 0.884, 0.836, 0.867, 0.914, 0.903, and 0.889, respectively, all indicating high levels of reliability.

4.2.2 Convergent Validity Analysis

This study assessed convergent validity using factor loadings and average variance extracted (AVE). The results indicate that the standardized factor loadings of all measurement items exceeded 0.70, with values ranging from 0.736 to 0.912, suggesting that all items adequately reflected their corresponding latent constructs.

Meanwhile, the AVE values of all constructs ranged from 0.642 to 0.787, all exceeding the recommended threshold of 0.50, indicating satisfactory convergent validity. Among the constructs, user trust had the highest AVE value of 0.787, suggesting that this construct possessed relatively strong explanatory power.

In addition, all variance inflation factor (VIF) values were below 3.3, indicating that no serious collinearity problem existed in the model.

Table 3: Reliability and Convergent Validity Assessment

Variable	Number of Items	Cronbach's α	CR	AVE
Recommendation Accuracy	3	0.884	0.921	0.745
Recommendation Transparency	3	0.836	0.890	0.670
Recommendation Reliability	3	0.867	0.909	0.714
User Trust	3	0.914	0.936	0.787
Perceived Usefulness	3	0.903	0.929	0.766
Behavioral Intention	3	0.889	0.923	0.750

4.2.3 Discriminant Validity Analysis

This study assessed discriminant validity using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). The results indicate that the square root of the AVE for each construct was greater than its correlations with other constructs, thereby satisfying the Fornell–Larcker criterion.

In addition, all HTMT values were below the recommended threshold of 0.90, with the highest value being 0.842, indicating satisfactory discriminant validity among the constructs and a high overall quality of the measurement model.

Table 4: Discriminant Validity Assessment

Variable	RP	RT	RR	TR	PU	BI
RP	0.863					
RT	0.612	0.819				
RR	0.587	0.594	0.845			
TR	0.648	0.632	0.661	0.887		
PU	0.603	0.589	0.692	0.704	0.875	
BI	0.618	0.574	0.650	0.682	0.746	0.866

4.3 Structural Model Assessment

This study employed SmartPLS 4.0 to conduct path analysis, and Bootstrapping with 5,000 resamples was used to test the significance of the path relationships. The model fit results indicate that the standardized root mean square residual (SRMR) value was 0.061, which is below the recommended threshold of 0.08, suggesting that the overall model fit was satisfactory.

The results show that recommendation accuracy, recommendation transparency, and recommendation reliability all had significant effects on users' cognitive evaluations, while user trust and perceived usefulness further influenced users' behavioral intentions. Specifically, recommendation accuracy had a significant positive effect on user trust ($\beta = 0.312$, $t = 5.684$, $p < 0.001$), indicating that when recommended content better matches users' interests and needs, users are more likely to develop trust in the platform's recommendation mechanism. Recommendation transparency also had a significant positive effect on user trust ($\beta = 0.163$, $t = 2.781$, $p < 0.01$), suggesting that the understandability of algorithmic recommendation logic can reduce users' perceived uncertainty regarding the "algorithmic black box."

Recommendation reliability had a significant positive effect on perceived usefulness ($\beta = 0.351$, $t = 6.104$, $p < 0.001$), indicating that users pay greater attention to the authenticity and credibility of recommended content. User trust also had a significant positive effect on perceived usefulness ($\beta = 0.428$, $t = 7.215$, $p < 0.001$), suggesting that when users have greater trust in recommendation systems, they are more likely to perceive the recommended content as practically helpful.

In addition, both user trust ($\beta = 0.291$, $t = 4.982$, $p < 0.001$) and perceived usefulness ($\beta = 0.517$, $t = 9.104$, $p < 0.001$) had significant positive effects on behavioral intention. Among these factors, perceived usefulness exerted a stronger influence on behavioral intention, indicating that users' final adoption of recommended content depends more heavily on their cognitive evaluation of the value and practical usefulness of the recommendations. Therefore, H1a, H1b, H2, H3, H4a, and H4b were all supported.

The R^2 results indicate that the explained variance for user trust was 0.463, for perceived usefulness was 0.572, and for behavioral intention was 0.648, suggesting that the model possessed satisfactory explanatory power.

Table 5: Structural Model Path Analysis Results

Hypothesis	Path Relationship	Path Coefficient (β)	t-value	p-value	Result
H1a	Recommendation Accuracy → User Trust	0.312	5.684	<0.001	Supported
H1b	Recommendation Transparency → User Trust	0.276	4.917	<0.001	Supported
H2	Recommendation Reliability → Perceived Usefulness	0.351	6.104	<0.001	Supported
H3	User Trust → Perceived Usefulness	0.428	7.215	<0.001	Supported
H4a	User Trust → Behavioral Intention	0.291	4.982	<0.001	Supported
H4b	Perceived Usefulness → Behavioral Intention	0.517	9.104	<0.001	Supported

4.4 Mediation Effect Analysis

This study further employed the Bootstrapping method to examine the mediating roles of user trust and perceived usefulness. The results indicate that user trust played a significant mediating role between recommendation accuracy and behavioral intention ($\beta = 0.091$, $t = 3.217$, $p < 0.01$), suggesting that AI algorithmic recommendation can further influence behavioral intention by enhancing user trust.

Perceived usefulness also played a significant mediating role between recommendation reliability and behavioral intention ($\beta = 0.182$, $t = 4.863$, $p < 0.001$), indicating that users are more likely to develop behavioral responses only when they perceive the recommended content as practically helpful.

In addition, user trust and perceived usefulness jointly formed a significant sequential mediating effect ($\beta = 0.126$, $t = 3.944$, $p < 0.001$), suggesting that AI algorithmic recommendation does not directly influence user behavior, but rather exerts its influence gradually through the cognitive pathway of "trust formation—value perception—behavioral response."

Table 6: Mediation Effect Analysis Results

Mediation Path	Indirect Effect (β)	t-value	p-value	95% Confidence Interval	Result
Recommendation Accuracy → User Trust → Behavioral Intention	0.091	3.217	<0.01	[0.038, 0.151]	Significant
Recommendation Transparency → User Trust → Behavioral Intention	0.080	2.984	<0.01	[0.031, 0.139]	Significant
Recommendation Reliability → Perceived Usefulness → Behavioral Intention	0.182	4.863	<0.001	[0.109, 0.257]	Significant
Recommendation Accuracy → User Trust → Perceived Usefulness → Behavioral Intention	0.069	3.506	<0.001	[0.031, 0.113]	Significant
Recommendation Transparency → User Trust → Perceived Usefulness → Behavioral Intention	0.061	3.128	<0.01	[0.026, 0.104]	Significant

4.5 Multi-Group Comparative Analysis

To further compare the differences in the influence mechanisms of AI algorithmic recommendation between consumption contexts and public health service contexts, this study employed the PLS-MGA method for intergroup comparative analysis.

The results show that the effect of recommendation accuracy on user trust was significantly stronger in the consumption context than in the public health service context ($\Delta\beta = 0.193$, $p < 0.05$), indicating that users of consumption-oriented platforms pay greater attention to the degree of matching between recommended content and their interests and needs.

In contrast, the effect of recommendation reliability on perceived usefulness was significantly stronger in the public health service context ($\Delta\beta = -0.186$, $p < 0.05$), suggesting that users in health service contexts pay greater attention to the authenticity, professionalism, and credibility of recommended content.

In addition, the effect of user trust on behavioral intention was more significant in the public health service context ($\Delta\beta = -0.166$, $p < 0.05$), whereas the effect of perceived usefulness on behavioral intention was more prominent in the consumption context ($\Delta\beta = 0.131$, $p < 0.05$).

Overall, the consumption context places greater emphasis on interest matching and personalized experiences, whereas the public health service context relies more heavily on the professionalism and trust mechanisms of recommendation systems.

Table 7: Multi-Group Comparative Analysis Results

Path Relationship	Consumption Context β	Public Health Service Context β	Path Difference	p-value	Conclusion
Recommendation Accuracy → User Trust	0.417	0.224	0.193	<0.05	Stronger in the consumption context
Recommendation Transparency → User Trust	0.241	0.318	−0.077	>0.05	Difference not significant
Recommendation Reliability → Perceived Usefulness	0.286	0.472	−0.186	<0.05	Stronger in the public health service context
User Trust → Perceived Usefulness	0.391	0.466	−0.075	>0.05	Difference not significant
User Trust → Behavioral Intention	0.218	0.384	−0.166	<0.05	Stronger in the public health service context
Perceived Usefulness → Behavioral Intention	0.563	0.432	0.131	<0.05	Stronger in the consumption context

5. DISCUSSION AND IMPLICATIONS

5.1 Discussion of the Findings

Based on both consumption contexts and public health service contexts, this study conducted a comparative analysis of the mechanisms through which AI algorithmic recommendation influences users' behavioral intentions. The findings indicate that recommendation accuracy, recommendation transparency, and recommendation reliability all further influence users' behavioral intentions through user trust and perceived usefulness, among which perceived usefulness has the most significant direct effect on behavioral intention. This suggests that in AI algorithmic recommendation environments, whether users accept platform-recommended content depends not only on the technical characteristics of the recommendation system itself, but also on users' cognitive evaluations of the value and practical usefulness of the recommendation results.

Further analysis reveals significant differences in the mechanisms of AI algorithmic recommendation across different contexts. In consumption contexts, recommendation accuracy exerts a stronger influence on user trust, indicating that users of consumption-oriented platforms place greater emphasis on the degree of matching between recommended content and their interests and preferences. Because consumption contexts are often characterized by entertainment attributes and interest-oriented features, users' behaviors are easily influenced by influencer recommendations, social interactions, and immersive recommendation experiences. When platforms can accurately identify users' preferences through algorithms and continuously recommend content that matches their interests and needs, users are more likely to develop platform dependence and behavioral acceptance. Therefore, algorithmic recommendation in consumption contexts places greater emphasis on personalized experiences and interest-driven mechanisms.

In contrast, in public health service contexts, recommendation reliability and user trust have more prominent effects on behavioral intention. This is mainly because health information involves strong professional attributes, uncertainty, and potential risks, making it difficult for users to quickly judge the authenticity and effectiveness of recommendation results in the same way as ordinary consumption content. In such contexts, users pay greater attention to whether the recommended content is professionally reliable, whether the recommendation source is trustworthy, and whether the platform possesses adequate health service capabilities. Therefore, algorithmic recommendation in public health service contexts relies more heavily on professionalism and trust mechanisms. Especially when users are making decisions regarding health information adoption and medical service selection, they tend to prioritize credibility judgments before further evaluating whether the recommended content is practically helpful.

In addition, the findings show that user trust and perceived usefulness play important mediating roles in the process through which AI algorithmic recommendation influences behavioral intention, forming a sequential cognitive pathway of “trust–usefulness–behavioral response.” This indicates that AI algorithmic recommendation does not directly determine user behavior, but gradually shapes behavioral responses by influencing users’ cognitive evaluations of recommendation systems. Fundamentally, algorithmic recommendation is not merely a technological recommendation mechanism, but also a cognitive influence mechanism.

5.2 Theoretical Implications

The theoretical contributions of this study are mainly reflected in the following aspects.

First, this study extends research on AI algorithmic recommendation from a cross-context comparative perspective. Existing studies have mainly focused on single contexts such as e-commerce consumption, short-video platforms, or online healthcare, while comparative analyses of the mechanisms of algorithmic recommendation across different contexts remain relatively limited. By simultaneously incorporating consumption contexts and public health service contexts, this study compares the differences in the mechanisms through which algorithmic recommendation influences users’ behavioral intentions across contexts, thereby helping to broaden the contextual boundaries of AI algorithmic recommendation research.

Second, this study further enriches the application of S-O-R theory in the field of AI algorithmic recommendation. The findings demonstrate that recommendation characteristics, including recommendation accuracy, recommendation transparency, and recommendation reliability, influence behavioral intention through user trust and perceived usefulness, thereby validating the theoretical logic of “external stimulus–cognitive evaluation–behavioral response.” At the same time, this study finds that user trust and perceived usefulness form a sequential mediating effect, suggesting that the formation of user behavior is a dynamic cognitive process rather than a simple technology acceptance process.

Finally, this study emphasizes the important role of contextual attributes in algorithmic recommendation research. The findings reveal that consumption contexts rely more heavily on interest matching and personalized experiences, whereas public health service contexts depend more strongly on professionalism and trust mechanisms. This indicates that the influence of AI algorithmic recommendation on user behavior is not merely a technological issue, but the result of the combined effects of contextual attributes, risk characteristics, and users’ cognitive mechanisms. Therefore, future research on algorithmic recommendation should pay greater attention to the differences in users’ behavioral logic across different contexts.

5.3 Practical Implications

First, platforms should further improve the accuracy of algorithmic recommendation systems to strengthen users’ interest matching and demand recognition capabilities. For consumption-oriented platforms, accurate recommendation can effectively improve user experience and behavioral conversion outcomes. Therefore, platforms should continuously optimize user profiling, behavioral analysis, and content matching mechanisms to improve the alignment between recommended content and users’ needs.

Second, platforms should enhance the transparency of algorithmic recommendation systems to reduce users’ perceived uncertainty regarding the “algorithmic black box.” At present, users’ lack of understanding of recommendation mechanisms can easily lead to perceptions of algorithmic manipulation and distrust. Therefore, platforms may improve the explainability of recommendation logic through recommendation explanations, recommendation label displays, and user preference settings, thereby enhancing users’ cognitive understanding and acceptance of algorithmic recommendation systems.

Third, in public health service contexts, professional review mechanisms and health information quality management should be further strengthened. Since health information involves strong professional attributes and potential risks, platforms need to strengthen physician qualification review, health content supervision, and recommendation information authenticity verification to avoid the spread of misinformation and algorithmic misguidance. At the same time, more standardized medical and health recommendation standards should be established to improve the overall credibility of platforms.

Finally, algorithm ethics and data privacy governance mechanisms should be further improved. Although AI algorithmic recommendation can improve platform service efficiency, it may also lead to problems such as privacy leakage, information cocoons, and algorithmic discrimination. Therefore, platforms should strengthen user data security protection, reasonably regulate data collection and usage behaviors, and establish a more transparent, fair, and sustainable algorithm governance system, thereby enhancing users' long-term trust and the sustainable development capability of platforms.

6. CONCLUSION AND FUTURE RESEARCH

6.1 Conclusion

Based on the S-O-R theory, the technology acceptance model, and trust theory, this study constructed a research model to examine how AI algorithmic recommendation influences users' behavioral intentions and conducted a comparative analysis from the perspectives of consumption contexts and public health service contexts. The results indicate that recommendation accuracy, recommendation transparency, and recommendation reliability all further influence users' behavioral intentions through user trust and perceived usefulness. Among these factors, perceived usefulness exerts the strongest effect on behavioral intention, while user trust plays an important mediating role between algorithmic recommendation characteristics and behavioral intention.

At the same time, this study finds significant differences in the mechanisms of AI algorithmic recommendation across different contexts. Consumption contexts rely more heavily on personalized recommendation, interest matching, and content experience, whereas public health service contexts depend more strongly on the professionalism, reliability, and trust mechanisms of recommendation systems. These findings indicate that the influence of AI algorithmic recommendation on user behavior is not a single technological process, but is jointly shaped by contextual attributes and users' cognitive mechanisms. This study provides practical references for digital platforms to optimize algorithmic recommendation services, improve user behavioral conversion efficiency, and enhance intelligent governance mechanisms in public health service contexts.

6.2 Limitations

Although this study has generated several meaningful findings, it still has certain limitations.

First, this study employed cross-sectional questionnaire data, which makes it difficult to fully capture the dynamic evolutionary process of users' cognition and behavior formation. Future studies may combine longitudinal research designs to further improve causal explanatory power.

Second, the sample of this study was mainly drawn from internet platform users, and limitations still exist regarding sample regions and user groups. Future studies may further expand the sample scope to improve the generalizability of the research findings.

Finally, this study mainly relied on self-reported user data and lacked validation using actual platform behavioral data. Future studies may incorporate platform clickstream, browsing, and interaction behavior data for multi-source data analysis in order to further improve the objectivity and external validity of the research conclusions.

6.3 Future Research Directions

Future research may be further developed in the following aspects.

First, future studies may introduce variables such as algorithm aversion, risk perception, and privacy concerns to explore the mechanisms through which complex cognitive factors influence users' acceptance of AI algorithmic recommendation.

Second, future studies may combine experimental methods, scenario simulation approaches, and platform behavioral data analysis methods to further improve the dynamic nature and contextual realism of the research.

Finally, future research may further compare the mechanisms through which AI algorithmic recommendation influences user behavior across different platform types, different age groups, and different cultural backgrounds, thereby enriching the research framework of digital platform user behavior.

FUNDING

This research was supported by the Jiangxi Provincial Social Science Foundation under the project "Research on the Mechanism Through Which AI Algorithmic Recommendation Influences Generation Z Consumer Behavior" (Grant No. 24GL65D), and the Jiujiang Social Science Foundation under the project "Research on the Application of AI Algorithmic Recommendation in Public Health Services in Jiujiang" (Grant No. 26YB111).

REFERENCES

[1] Benbasat, I., & Wang, W. (2005). Trust in and adoption of online recommendation agents. *Journal of the Association for Information Systems, 6*(3), 72–101.

[2] Chew, H. S. J., Achananuparp, P., & Periaswamy, S. (2022). Perceptions and needs of artificial intelligence in health care to increase adoption: Scoping review. *Journal of Medical Internet Research, 24*(1), e32939. https://doi.org/10.2196/32939

[3] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

[4] Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 144*(1), 114–126. https://doi.org/10.1037/xge0000033

[5] Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90. https://doi.org/10.2307/30036519

[6] Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer. https://doi.org/10.1007/978-3-030-80519-7

[7] Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling* (PLS-SEM) (3rd ed.). Sage.

[8] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

[9] Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International Marketing Review, 33*(3), 405–431. https://doi.org/10.1108/IMR-09-2014-0304

[10] Kauttonen, J., Rousi, R., & Alamäki, A. (2025). Trust and acceptance challenges in the adoption of AI applications in health care: Quantitative survey analysis. *Journal of Medical Internet Research, 27*, e65567. https://doi.org/10.2196/65567

[11] Knijnenburg, B. P., Willemsen, M. C., Gantner, Z., Soncu, H., & Newell, C. (2012). Explaining the user experience of recommender systems. *User Modeling and User-Adapted Interaction, 22*(4–5), 441–504. https://doi.org/10.1007/s11257-011-9118-4

[12] Komiak, S. Y. X., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly, 30*(4), 941–960. https://doi.org/10.2307/25148760

[13] Konstan, J. A., & Riedl, J. (2012). Recommender systems: From algorithms to user experience. *User Modeling and User-Adapted Interaction, 22*(1–2), 101–123. https://doi.org/10.1007/s11257-011-9112-x

[14] Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes, 151*, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

[15] Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. MIT Press.

[16] Qin, H. (2024). Examining the impact of personalization and carefulness in AI-generated health advice: Trust, adoption, and insights in online healthcare consultations. *Telematics and Informatics, 93*, 102174. https://doi.org/10.1016/j.tele.2024.102174

[17] Qin, M., Zhu, W., Zhao, S., & Zhao, Y. (2022). Is artificial intelligence better than manpower? The effects of different types of online customer services on customer purchase intentions. *Sustainability, 14*(7), 3974. https://doi.org/10.3390/su14073974
[18] Rosenbacke, R., Melhus, Å., McKee, M., & Stuckler, D. (2024). How explainable artificial intelligence can increase or decrease clinicians' trust in AI applications in health care: Systematic review. *JMIR AI, 3*, e53207. https://doi.org/10.2196/53207
[19] Sarstedt, M., Ringle, C. M., & Hair, J. F. (2022). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of market research* (pp. 587–632). Springer. https://doi.org/10.1007/978-3-319-57413-4_15
[20] Shin, D. (2020). User perceptions of algorithmic decisions in the personalized AI system: Perceptual evaluation of fairness, accountability, transparency, and explainability. *Journal of Broadcasting & Electronic Media, 64*(4), 541–565. https://doi.org/10.1080/08838151.2020.1843357
[21] Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies, 146*, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551
[22] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540
[23] Wang, W., & Benbasat, I. (2007). Recommendation agents for electronic commerce: Effects of explanation facilities on trusting beliefs. *Journal of Management Information Systems, 23*(4), 217–246. https://doi.org/10.2753/MIS0742-1222230410
[24] Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly, 31*(1), 137–209. https://doi.org/10.2307/25148784
[25] Xu, Y., & Chen, L. (2025). Personalized recommendations and consumer trust: The role of perceived control and locus of control. *Acta Psychologica, 261*, 105936. https://doi.org/10.1016/j.actpsy.2025.105936
[26] Zhang, B., & Sundar, S. S. (2019). Proactive versus reactive personalization: Can customization of privacy enhance user experience? *International Journal of Human-Computer Studies, 128*, 86–99. https://doi.org/10.1016/j.ijhcs.2019.03.002
[27] Zhang, X., Guo, X., Lai, K. H., Guo, F., & Li, C. (2014). Understanding gender differences in m-health adoption: A modified theory of reasoned action model. *Telemedicine and e-Health, 20*(1), 39–46. https://doi.org/10.1089/tmj.2013.0092
[28] Zhang, Y., & Chen, X. (2020). Explainable recommendation: A survey and new perspectives. *Foundations and Trends in Information Retrieval, 14*(1), 1–101. https://doi.org/10.1561/1500000066
[29] Zhao, Y., Wang, A., & Sun, Y. (2020). Technological environment, virtual experience, and MOOC continuance: A stimulus–organism–response perspective. *Computers & Education, 144*, 103721. https://doi.org/10.1016/j.compedu.2019.103721
[30] Zhou, T. (2011). Examining the critical success factors of mobile website adoption. *Online Information Review, 35*(4), 636–652. https://doi.org/10.1108/14684521111161972
[31] Zhou, T. (2013). An empirical examination of continuance intention of mobile payment services. *Decision Support Systems, 54*(2), 1085–1091. https://doi.org/10.1016/j.dss.2012.10.034
[32] Zhu, W., Ouyang, P., & Kong, M. (2024). Research on the evolution mechanism of intelligent manufacturing transformation of Chinese pharmaceutical manufacturing enterprises based on system dynamics. *Heliyon, 10*(13), e33825. https://doi.org/10.1016/j.heliyon.2024.e33825
[33] Zhu, W., Ouyang, P., Ke, X., Qiu, S., Li, S., & Jiang, Z. (2024). NK model simulation study of intelligent manufacturing transformation path selection in pharmaceutical manufacturing enterprises. *Scientific Reports, 14*(1), 19646. https://doi.org/10.1038/s41598-024-70567-2
[34] Zhu, Y. Q., & Chang, J. H. (2016). The key role of relevance in personalized advertisement: Examining its impact on perceptions of privacy invasion, self-awareness, and continuous use intentions. *Computers in Human Behavior, 65*, 442–447. https://doi.org/10.1016/j.chb.2016.08.048