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Study on the Behavioral Motives of Algorithmic Avoidance in Intelligent Recommendation Systems

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ABSTRACT

Through an exploration of the underlying mechanisms driving users' algorithmic avoidance in intelligent recommendation systems, this study aims to facilitate a positive interaction between users and technology, providing theoretical guidance for the efficient operations of enterprises using intelligent recommendation systems. The research integrates the theories of information ecology and psychological resistance, establishing a model of influencing factors on users' algorithmic avoidance in intelligent recommendation systems. Utilizing a structural equation model, the study conducts analysis and validation on data collected from 506 questionnaires. The findings reveal that algorithmic transparency and perceived manipulation significantly impact the users' algorithmic avoidance in intelligent recommendation systems. The sense of being manipulated emerges as a crucial psychological factor leading to algorithmic avoidance, playing a complete mediating role in the influence of information quality, homogeneous recommendation, and algorithmic transparency on algorithmic avoidance.

KEYWORDS

Intelligent Recommendation, Algorithmic Avoidance, Behavioral Motives, Information Ecology, Psychological Resistance

INTRODUCTION

Algorithms are the core driving force behind the development of artificial intelligence, constituting a pivotal driving factor in contemporary enterprises' digital management and the construction of intelligent societies (Shin, 2021a; Shin, Rasul, et al., 2022). Intelligent recommendation systems utilize artificial intelligence algorithms to analyze extensive user data, enabling the system to provide each user with products, services, or information tailored to their interests and needs. This represents a typical manifestation of algorithmic applications (Shin, Kee, et al., 2022). Intelligent recommendation services, formed through the application of algorithmic technology, have become a critical element in shaping the core competitiveness of internet platforms. Increasingly, businesses are adopting algorithms to optimize product and service design, enhance user experiences, and stand out in the intense landscape of commercial competition.

Intelligent recommendation systems, employing personal data mining to capture user demands, offer personalized services and have been extensively applied across various domains, such as

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social media, e-commerce, shopping, and news, deeply infiltrating multiple aspects of public life. Intelligent recommendation technology has transformed information retrieval, effectively alleviating the "information overload" phenomenon in the era of big data (Bobadilla et al., 2013). However, the widespread adoption of this technology has also brought numerous risks, drawing attention and concern due to adverse effects such as personal privacy breaches, information cocoons, internet addiction, algorithmic price discrimination, and excessive consumption induced by algorithmic recommendations (Han et al., 2023; Xu, 2022).

Although policies, regulations, and systems related to algorithm governance are gradually improving, these enhancements do not wholly alleviate individuals' negative emotions toward algorithms. Survey results indicate variations in people's acceptance of algorithmically recommended content (Smith, 2018). Personal negative emotions toward algorithms are not only related to objective algorithmic risks but are also significantly influenced by individuals' subjective perceptions. Avoidance behavior is considered one of the fundamental responses of organisms to environmental stimuli (Gilbert et al., 1998; Schneirla, 1959). Users' information avoidance behavior helps reduce individual cognitive burdens and alleviate adverse emotions arising from frequent algorithmic recommendations (Case et al., 2005). It is seen as an effective means of risk coping and emotion alleviation (Zhao & Liu, 2021).

For businesses, achieving digital transformation requires addressing not only the capital and technological barriers to innovation but also the "user barriers" that arise after algorithm implementation. Gaining a deeper understanding of the reasons and impacts of individuals' negative emotions toward algorithms can help businesses better overcome these barriers and fully leverage the positive effects of algorithms. Researching questions such as "Why do people engage in algorithmic avoidance?" and "Under what conditions is users' algorithmic avoidance strengthened or weakened?" can assist businesses in understanding obstacles to organizational development posed by algorithms. It can also aid national governments in formulating new guidelines for advancing digitalization and promoting algorithmic risk prevention and governance. Consequently, this study aims to explore the motivations influencing users' algorithmic avoidance behavior in intelligent recommendation systems, with the expectation of fostering positive interaction between users and technology and providing guidance for the effective development of enterprises using these systems.

LITERATURE REVIEW

Algorithmic avoidance refers to users' manifestation of negative emotions, unfavorable attitudes, and a tendency to avoid recommendations and services provided by algorithms (Ettlinger, 2018). Existing research in this area primarily covers domains such as healthcare, e-commerce, and social media. Different types of products (hedonic vs. utilitarian) impact consumers' aversion to algorithms. For hedonic products, consumers exhibit a higher aversion to artificial intelligence algorithm recommendations than human recommenders (Longoni & Cian, 2022). Additionally, consumers' need for uniqueness can influence their attitudes toward algorithms. When patients perceive that artificial intelligence algorithms may overlook their unique characteristics, they are likely to resist the adoption of such algorithms (Longoni et al., 2019).

While scholars have delved into users' algorithmic avoidance, relevant research suggests that individual, situational, and algorithmic factors can influence users' algorithmic avoidance behaviors. Regarding individual factors, studies have primarily explored the impact of gender (Araujo et al., 2020), age (Logg et al., 2019), and the Big Five personality traits (van Esch et al., 2021) on algorithmic avoidance. Research on situational factors has focused on the influence of product types (Longoni & Cian, 2022) and task difficulty (Granulo et al., 2021). Research on algorithmic factors has predominantly examined the effects of algorithmic anthropomorphism (Yam et al., 2021), algorithmic role (Möhlmann et al., 2021), and algorithmic interpretability (Parent-Rocheleau & Parker, 2022) on algorithmic avoidance.

Existing research has predominantly focused on algorithmic avoidance in robotics, with scarce literature addressing the factors associated with users' algorithmic avoidance behaviors in intelligent recommendation systems. Negative usage behaviors stemming from algorithmic avoidance have received relatively little attention. This study utilizes a questionnaire to collect data. It employs structural equation modeling (SEM) to comprehensively analyze the mechanisms and influencing factors behind the formation of algorithmic avoidance behaviors in intelligent recommendation systems. The goal is to foster a positive interaction between users and technology and provide guidance for the effective development of enterprises using intelligent recommendation systems.

THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

In our research, we utilize information ecology theory as a theoretical foundation to guide the development of our framework and hypotheses. Information ecology theory employs ecological perspectives and viewpoints to analyze informatics content, emphasizing the complex relationships among internal elements from a systemic perspective. It considers information ecology as the sum of interactions among information, information users, the information environment, and information technology, underscoring the active state of interaction among these components (Horton, 1978; Nardi & O'Day, 2000; Xie, 2023). The theory posits that human behavior results from the collective influence of information, information environment, and information technology, exhibiting robust explanatory power and applicability in the realm of human behavior (Lippitt, 1939; Yuan & Wang, 2022). The information behavior of information individuals and their interactions with other elements constitute pivotal issues in the information ecology theory research agenda (Bruns, 2017). The intelligent recommendation information ecosystem is formed through activities of intelligent recommendation information services, representing the outcome of information entities engaging in information interaction within a specific social environment facilitated by modern network technologies. This aligns with the study of how various elements within the information ecology perspective interact with each other and collectively influence the system.

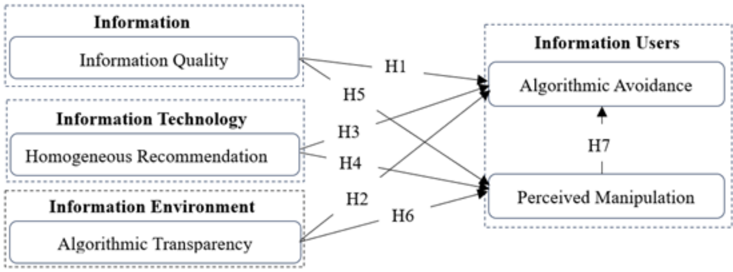
In the intelligent recommendation information ecosystem, users' information behavior is influenced by factors such as information users, information quality, information environment, and information technology. Information quality is the primary concern for users of intelligent recommendation systems, significantly affecting their perception of recommendation quality and their trust in recommendation sources (Kunkel et al., 2019). Algorithmic transparency and homogeneous recommendation are essential characteristics of intelligent recommendation algorithms, closely linked to user experience (Wang et al., 2021). The feeling of being manipulated, a core expression of psychological resistance, can impact user behavior.

Grounded in information ecology theory, integrating a psychological resistance perspective, and drawing upon a substantial body of relevant literature, this study considers information quality as a factor within the information dimension, algorithm transparency as a factor within the information environment dimension, homogeneous recommendation as a factor within the information technology dimension, and perceived manipulation as a factor within the information user dimension. The research investigates the impact mechanisms of information quality, algorithmic transparency, homogeneous recommendation, and perceived manipulation on users' algorithmic avoidance behavior in intelligent recommendation systems. Consequently, we have devised the hypothesis framework for this study, as illustrated in Figure 1.

Information Quality, Algorithmic Transparency, Homogeneous Recommendation, and Algorithmic Avoidance

Low-quality information on intelligent recommendation systems can influence users' algorithmic avoidance. When users obtain information through these systems, the quality of the recommended content influences their information acquisition and discernment, potentially triggering algorithmic

Figure 1. Research model for algorithmic avoidance



avoidance. Forms of low-quality information, such as misinformation, redundancy, and excessive information, can lead users to overlook or misjudge information. Compared to human predictions, incorrect algorithmic predictions may cause individuals to strongly favor algorithmic avoidance (Dietvorst et al., 2015). Consequently, this paper posits the following hypothesis:

H1. The information quality of recommended content on intelligent recommendation systems exerts a significantly negative impact on users' algorithmic avoidance tendencies within the domain of intelligent recommendation systems.

Algorithmic transparency refers to the extent of user awareness regarding how intelligent recommendation systems execute algorithmic recommendations. This encompasses the degree to which users are informed about the methodology of algorithmic recommendations on the system, as well as their understanding of the scope, management, and potential consequences associated with the collection of personal information by the system (Shin & Park, 2019). When users perceive the algorithm as exhibiting fairness, accountability, transparency, and explainability, they regard it as more reliable and beneficial (Shin, 2020; Shin, 2021b). The opaqueness inherent in the algorithmic recommendation mechanism, coupled with the existence of algorithmic black boxes, can evoke unease and anxiety in users (Langer et al., 2018). As data collection methods become more invasive and lack transparency and accountability, users may develop a sense of exploitation (Barth & De Jong, 2017). At this juncture, data collection practices may pose a threat to users' ownership of personal data, affecting their sense of control and triggering strong psychological resistance, leading to users' algorithmic avoidance (Martin, 2020). The opaqueness of recommendation systems and the potential infringement on user privacy prompt demands for increased transparency from recommendation systems and businesses regarding the collection and processing of personal information. Implementing information transparency can effectively alleviate users' privacy concerns (Hsu & Lin, 2016), reducing instances of algorithmic avoidance behavior. Therefore, this paper posits the following hypothesis:

H2. Algorithmic transparency significantly negatively influences users' algorithmic avoidance behavior in intelligent recommendation systems.

Although algorithmic recommendations can enhance efficiency to a certain extent, intelligent recommendation systems continually present users with information tailored to their preferences, aiming to increase user engagement and reading time. However, this highly homogeneous information flow effectively forms a filtered "bubble," resulting in an "information cocoon" that reduces the space for user choice. This can lead to user discomfort and foster algorithmic avoidance (Latzer & Festic, 2019). The severe homogenization of content, coupled with low timeliness, increases users' cost of information filtering, diminishing the perceived value of content acquisition. This may even induce a sense of loss of control (Edmunds & Morris, 2000), subsequently leading to feelings of fatigue, anxiety, and other negative emotions (Misra & Stokols, 2012). When users frequently receive information related to their online behavior, especially high-sensitivity information, the singularity, homogeneity, and limitations of such information can heighten concerns about observing or recording personal information against their will. This positively influences users' sense of being manipulated, resulting in algorithmic avoidance. Therefore, this paper proposes the following hypothesis:

H3. Homogenization in recommendations significantly and positively influences users' algorithmic avoidance behavior in intelligent recommendation systems.

Information Quality, Algorithmic Transparency, Homogeneous Recommendation, and Perceived Manipulation

Perceived manipulation is a psychological mechanism and response generated when a user's cognitive process is forcibly interrupted. It refers to the user's perception of being compelled to provide or receive certain information by intelligent recommendation systems, as well as the perception of the system influencing the user's thoughts or beliefs by guiding the flow of information (Edwards et al., 2002). This constitutes a core manifestation of psychological resistance. The direct consequence of intelligent recommendations is the continuous delivery of information that aligns with the user's preferences, while content users have not previously engaged with remains unrecommended. Rule-based procedures within intelligent recommendation systems aim to reduce the complexity of data in automated decision-making, attempting to define users' intricate information needs through the use of labeling and user profiles.

The underlying principle of intelligent recommendation algorithms leads to users repeatedly receiving content on the same theme, failing to meet their demands for comprehensive and diverse information. This misalignment in information needs traps users in an "information cocoon," progressively narrowing their informational perspective (Bucher, 2012). As a result, users may lose access to a broader range of knowledge resources they previously engaged with. When users perceive that homogenization in recommendations creates an "information cocoon," they experience perceived manipulation, which triggers psychological resistance. In extreme cases, users may abandon the algorithmic platform to circumvent algorithmic influence (Kivetz, 2005).

The higher the information quality of content an intelligent recommendation system recommends, the better it can fulfill user needs. Consequently, this can mitigate users' feelings of compulsion and intentions of manipulation. Therefore, this paper posits the following hypotheses:

H4. Homogenization in recommendations significantly and positively influences the sense of being manipulated among users of intelligent recommendation systems.
H5. Information quality significantly and negatively impacts the sense of being manipulated among users of intelligent recommendation systems.

Digital technology has introduced both digital benefits and hegemony, along with technological drawbacks such as information leakage, algorithmic black holes, and data dictatorship. This has placed ordinary members of society in a state of manipulation and transparency. Intelligent recommendation algorithms function as a technological black box, where users passively receive information without the ability to control or predict the next recommended piece. These systems may exploit personal information to forcibly guide or interweave the flow of information, quickly inducing users to experience coercive sensations and a sense of being manipulated (Edwards et al., 2002). Users may be compelled to grant specific permissions to access services, unwittingly activate unnecessary permissions, or struggle to find options to turn off algorithmic recommendations. This can lead to a heightened sense of being manipulated. Therefore, this paper posits the following hypothesis:

H6. Algorithmic transparency significantly negatively influences the sense of being manipulated among users of intelligent recommendation systems.

Perceived Manipulation and Algorithmic Avoidance

Brehm (1966) noted that when individuals perceive a threat to their freedom, they experience psychological reactance, wherein they attempt to alleviate the threat, avoid further loss, and reconstruct their freedom. An individual's psychological state is closely related to their intentions and behaviors, providing insights into the internal mechanisms of behavior. Psychological reactance positively affects user behaviors, such as ignoring and blocking information (Youn & Kim, 2019). The substantial volume of information pushed by intelligent recommendation systems can make users feel misled and deceived, triggering psychological reactance and resulting in negative usage behaviors. When individuals experience psychological reactance, they typically employ direct or indirect strategies to cope with the perceived threat and attempt to restore their freedom, leading to cognitive and behavioral avoidance. The algorithmic recommendation mechanism forces users to relinquish their autonomous judgment as information receivers, turning them into manipulated individuals who have lost the right to choose information. Such manipulation may be subtle and difficult to perceive. When users in intelligent recommendation systems perceive a loss of their right to select information, are constrained to passively receive algorithmic recommendations, and encounter compulsory "value indoctrination" in personalized recommendations, they develop a strong sense of being manipulated, which increases their perceived threat (Kim & Kim, 2018). Consequently, users may resist the algorithm. Therefore, this paper posits the following hypotheses:

H7. The perceived sense of being manipulated significantly and positively influences algorithmic avoidance behavior among users of intelligent recommendation systems.
H8. The perceived sense of being manipulated is a significant mediating factor between information quality and algorithmic avoidance.
H9. The perceived sense of being manipulated mediates between homogeneous recommendation and algorithmic avoidance.
H10. The perceived sense of being manipulated mediates between algorithmic transparency and algorithmic avoidance.

METHODOLOGY

Questionnaire Survey

In alignment with Shareef et al. (2016), to ensure the structural validity of the measurements, the items were developed based on existing scales that have been empirically tested and validated in prior studies and adapted to the context of intelligent recommendation systems. All items were measured using a Likert 7-point scale (1 = Strongly Disagree; 7 = Strongly Agree). Specifically, the information quality scale was adapted from DeLone and McLean (2003), the homogeneous recommendation scale was adapted from Vogler et al. (2020) and Baden and Tenenboim-Weinblatt (2017), the algorithmic transparency scale was drawn from Durcikova and Gray (2009), the perceived manipulation scale was modified from Edwards et al. (2002) and Henrie and Taylor (2009), and the algorithmic avoidance scale was derived from Xie et al. (2022).

Additionally, in the final section of the questionnaire, we collected respondents' demographic information, including age, gender, type of intelligent recommendation usage, and educational level. The questionnaire was initially developed in English, reflecting its structure and items based on English literature. For the survey conducted in China, the research team—proficient in both languages—carefully translated the questionnaire into Chinese (Huang et al., 2023; Zhang et al., 2021).

After completing the measurement scale design, an online survey was created on the Wen-juan-wang[1] survey platform. To ensure validity, we invited three renowned experts in the field of information systems to evaluate the content validity of the questionnaire (Hsu & Lee, 2023). They assessed the logical consistency of measurement items, evaluated their comprehensibility, and provided feedback for adjustments and modifications (Chauhan et al., 2023; Jebarajakirthy et al., 2022). Subsequently, we randomly recruited 30 users with experience using apps like Douyin, Xiaohongshu, and Toutiao for research to test the scale's validity and finalize the survey items for the investigation (Cui et al., 2022). The Cronbach's alpha values for all latent variables exceeded 0.7, indicating good construct reliability.

Data Collection

Through a survey targeting users with substantial experience in intelligent recommendation software usage, we collected data to empirically test the hypotheses. Using a survey for data collection is well-established in management science, offering a reliable method for gathering extensive individual-level data (Ertekin et al., 2020; Sila, 2018).

In China, intelligence recommendation technology is widely used in various aspects of daily life, including social media, e-commerce, and news consumption. Platforms such as Douyin, Xiaohongshu, Bilibili, Zhihu, Taobao, and Toutiao are successful mobile applications employing intelligent recommendation systems in these domains. These platforms hold significant market positions and have substantial influence. Therefore, this research focuses on users of these platforms and conducts an investigation specifically targeted at this demographic.

The formal survey commenced at the end of October 2023. Participants were required to have at least one year of experience with the platforms to ensure they had sufficient exposure to and understanding of intelligent recommendation algorithms. Data collection employed both online and offline methods.

In the offline phase, conducted at various universities in Guangzhou, we used a "random interception–oral inquiry–gift giving" approach to recruit undergraduate students. We distributed 420 questionnaires, of which 358 were successfully collected. Two weeks later, we employed a snowball sampling technique to invite individuals already in the workforce to participate online (https://www.wenjuan.com/).

All participants voluntarily took part, with an incentive of a chance to win cash red packets for completing the survey. To ensure data quality, attention-check questions were included. Post-survey analysis showed no significant differences between online and offline responses regarding the measurement items. In total, 723 questionnaires were collected, 365 from online and 358 from offline sources. After excluding invalid responses—those from participants with less than one year of platform usage, uniform answers, failure to pass attention checks, and completion times under 180 seconds—a final dataset of 506 valid questionnaires was retained.

DATA ANALYSIS AND RESULTS

Demographics

The demographic characteristics of the respondents are summarized in Table 1. The gender distribution of the survey respondents shows that females make up 34.98% of the sample, while males account for 65.02%. The largest age group is 18–25 years, with 373 respondents, representing

Table 1. Demographic characteristics (N = 506)

Category	Sub Category	Frequency	Percent (%)
Gender	Male	329	65.02
	Female	177	34.98
Age(years)	< 18	10	1.98
	18–25	373	73.71
	26–35	93	18.38
	36–45	30	5.93
Education	Junior high school and below	7	1.38
	High school	64	12.65
	Associate degree and bachelor's degree	366	72.33
	Postgraduate degree	69	13.64
Intelligent recommendation platform	TikTok	255	50.40
	Xiaohongshu	79	15.61
	Bilibili	83	16.40
	Zhihu	52	10.28
	Taobao	25	4.94
	Toutiao	12	2.37

73.71% of the valid sample. The next largest age group is 26–35, comprising 18.38% of the valid sample. Regarding educational qualifications, 366 respondents hold a college or undergraduate degree, constituting 72.33% of the total valid sample. Among the types of intelligent recommendation software used, TikTok is the most frequently used, representing 50.40% of the valid sample.

Common Method Bias

When using the same method to measure different variables, there is a risk of common method bias, which can lead to spurious correlations among the variables (Lindell & Whitney, 2001). To address this issue, the study employed a multi-item measurement approach for assessing various constructs and strategically placed each variable in separate sections of the questionnaire. Additionally, data were collected online and offline, and the questionnaire was administered at different time intervals to further mitigate potential biases.

For statistical analysis, this study followed the methodologies proposed by Korsgaard and Roberson (1995) and Mossholder et al. (1998) to examine common method bias. A confirmatory factor analysis was conducted with all items loaded onto a single factor. The results showed that the fit indices of this single-factor model ($\chi^2 = 1108.899$, $\chi^2/df = 10.662$) were significantly worse compared to the fit indices of the five-factor measurement model used in this study ($\chi^2 = 331.166$, $\chi^2/df = 3.523$), indicating that severe common method bias was not present.

Additionally, following Richardson et al. (2009), a two-factor model was tested with a common method factor. This model's fit ($\chi^2 = 215.173$, Tucker–Lewis index [TLI] = 0.978, comparative fit index [CFI] = 0.986, root mean square error of approximation [RMSEA] = 0.059) was improved compared to the original five-factor model ($\chi^2 = 331.166$, TLI = 0.969, CFI = 0.975, RMSEA = 0.071). However, the improvement did not exceed the 0.05 threshold suggested by Bagozzi and Yi (1990) (ΔTLI = 0.009, ΔCFI = 0.011, ΔRMSEA = 0.012), indicating that the common method factor did not significantly enhance the model's fit. Overall, this study did not find substantial evidence of common method bias.

Table 2. Measurement scale statistics

Constructs	Items	Item loading	Cronbach's alpha	CR	AVE
Information quality (IQ)	IQ1	0.878	0.924	0.9222	0.7982
	IQ2	0.932			
	IQ3	0.869			
Homogeneous recommendation (HR)	RH1	0.917	0.939	0.9392	0.8375
	RH2	0.934			
	RH3	0.894			
Algorithmic transparency (AT)	AT1	0.918	0.921	0.921	0.7955
	AT2	0.89			
	AT3	0.867			
Perceived manipulation (PM)	PM1	0.893	0.937	0.9368	0.7876
	PM2	0.889			
	PM3	0.857			
	PM4	0.91			
Algorithmic avoidance (AA)	AA1	0.895	0.923	0.9241	0.8023
	AA2	0.888			
	AA3	0.904			

Measurement Model

Reliability refers to the consistency and dependability of the results obtained from a measurement scale. It is evaluated through composite reliability (CR) and internal consistency coefficients (Cronbach's alpha) derived from latent variables. Generally, CR and Cronbach's alpha values of at least 0.7 indicate a satisfactory reliability level in the measurement model (Kumari, 2022; Straub et al., 2004; Xu et al., 2022). As shown in Table 2, the minimum CR value is 0.921, and the minimum Cronbach's alpha value is also 0.921, demonstrating a high level of reliability in the measurement model.

The effectiveness of the measurement model is assessed through content validity, convergent validity, and discriminant validity (Straub et al., 2004). Convergent validity is evaluated using the average variance extracted (AVE) and the standardized loadings of each measurement item on its corresponding latent variable (Changchit et al., 2023; Tseng et al., 2023). A measurement scale demonstrates good convergent validity when both the AVE and the standardized loadings exceed 0.5 (Straub et al., 2004). Discriminant validity is assessed by comparing the square root of AVE with the inter-variable correlation coefficients. A measurement scale is considered to have good discriminant validity if the square root of AVE is greater than the correlation coefficients between the variable and other variables (Straub et al., 2004).

All measurement items in this study were adapted from existing literature and underwent a preliminary investigation on a small scale before the extensive survey. This provides a solid basis for asserting that the scale's content is clear, precise, and effective. As shown in Table 2, the minimum AVE value is 0.7876, and the minimum standardized loading coefficient of each measurement item on its corresponding latent variable is 0.867. These results indicate that the measurement model exhibits strong convergent validity. Additionally, Table 3 demonstrates that the square root of AVE for each latent variable exceeds the correlation coefficients between that variable and other latent variables, confirming that the measurement model has good discriminant validity.

Table 3. Correlation and square roots of AVE

Constructs	IQ	RH	AT	PM	AA
Information quality (IQ)	0.893				
Homogeneous recommendation (HR)	–0.824	0.915			
Algorithmic transparency (AT)	0.890	–0.794	0.892		
Perceived manipulation (PM)	–0.882	0.867	–0.883	0.887	
Algorithmic avoidance (AA)	–0.890	0.846	–0.882	0.854	0.896

Table 4. The degree of model fit

Fit statistics	Criterion of fitness	Structural model
X^2/df	< 5 (Sun et al., 2022)	3.523
GFI	> 0.9	0.926
RMSEA	< 0.08 (Hair et al., 2014)	0.071
IFI	> 0.9 (Bollen, 1989)	0.975
CFI	> 0.9 (Bentler, 1990)	0.975
TLI	> 0.9 (Hu & Bentler, 1999)	0.969
AGFI	> 0.8	0.893

In addition, we assessed the normality of all measured items. The standard deviations ranged from 1.02024 to 1.25922, indicating relatively low dispersion in the sample. The skewness values for all variables were less than 1, and the kurtosis values were below 2, suggesting that the sample data generally conforms to a normal distribution (Kline, 1998). These results meet the basic requirements for data analysis, thus allowing for the subsequent relevant analyses.

Structural Model

Fit analysis of the model assesses how well the model aligns with the data (Mossberger et al., 2013). In this study, we used Amos software for the analysis, and the overall fit indices for the model are presented in Table 4. The results indicate that all fit indices meet the fitness criteria, demonstrating a favorable level of model fit.

Results

Multivariate normal distribution and a sufficiently large sample size (typically between 200 and 500, with a minimum of 200 cases) are essential assumptions for applying SEM (Boomsma & Hoogland, 2001; Schumacker & Lomax, 2004). Ringle et al. (2009) suggest that when data meet the normal distribution assumption, covariance-based SEM (CB-SEM) should be prioritized. Since the sample data in this study passed the normality test, exhibited no severe skewness, and met the large sample size requirement, CB-SEM is deemed appropriate for hypothesis testing. Given that Amos is well-suited for covariance-based structural equation analysis, we employed Amos software to conduct SEM analysis on the main effects model, using maximum likelihood estimation for hypothesis testing. The path coefficients for all hypothesized relationships in the model are presented in Table 5 and Figure 2.

According to Table 5, most hypothesized paths are significant except for "information quality → algorithmic avoidance" and "homogeneous recommendation → algorithmic avoidance." Specifically, the data reveal the following significant relationships:

Table 5. Results of the path analysis

	Path coefficient β	S.E.	C.R.	P values	Conclusion
H1: Algorithmic avoidance ← Information quality	–0.059	0.086	–0.719	0.472	Not supported
H2: Algorithmic avoidance ← Algorithmic transparency	–0.248	0.059	–3.998	***	Supported
H3: Algorithmic avoidance ← Homogeneous recommendation	–0.054	0.056	–0.938	0.348	Not supported
H4: Perceived manipulation ← Homogeneous recommendation	0.400	0.040	9.880	***	Supported
H5: Perceived manipulation ← Information quality	–0.437	0.068	–6.726	***	Supported
H6: Perceived manipulation ← Algorithmic transparency	–0.172	0.056	–2.929	0.003	Supported
H7: Algorithmic avoidance ← Perceived manipulation	0.729	0.103	7.098	***	Supported

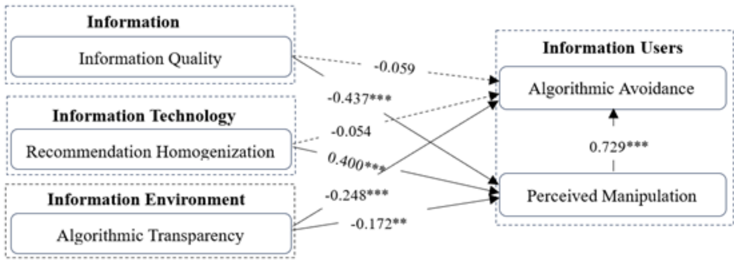
- Information quality significantly negatively influences users' perceived manipulation ($\beta = -0.437$, $P < 0.001$)
- Homogeneous recommendations significantly positively influence users' perceived manipulation ($\beta = 0.4$, $P < 0.001$)
- Algorithmic transparency significantly negatively influences users' perceived manipulation ($\beta = -0.172$, $P < 0.01$)
- Algorithmic transparency significantly negatively influences users' algorithmic avoidance ($\beta = -0.248$, $P < 0.001$)
- Users' perceived manipulation significantly positively influences their algorithmic avoidance ($\beta = 0.729$, $P < 0.01$).

These results support hypotheses H2, H4, H5, H6, and H7. In the holistic model, the path coefficient for the effect of information quality on algorithmic avoidance is not significant, but it is smaller than the coefficient for its effect on perceived manipulation. This suggests that perceived manipulation fully mediates the relationship between information quality and algorithmic avoidance, with information quality negatively influencing algorithmic avoidance. Similarly, the path coefficient for the effect of homogeneous recommendations on algorithmic avoidance is not significant in the overall model. Still, it is smaller than the coefficient for its effect on perceived manipulation. This implies that perceived manipulation fully mediates the relationship between homogeneous recommendations and algorithmic avoidance, with homogeneous recommendations positively influencing algorithmic avoidance.

In this study, we assessed the mediation effects of perceived manipulation using the method proposed by MacKinnon (2012). Specifically, we examined how perceived manipulation mediates the relationship between information quality and algorithmic avoidance, homogenization of recommendations and algorithmic avoidance, as well as algorithmic transparency and algorithmic avoidance. The mediation effect analysis was performed using the bootstrapping method in Amos, with 5,000 repeated samples drawn at a 95% confidence level to enhance the accuracy of the estimates. The results are detailed in Table 6.

According to Table 6, the bias-corrected and percentile confidence intervals for the paths "information quality → perceived manipulation → algorithmic avoidance" and "homogeneous recommendation → perceived manipulation → algorithmic avoidance" do not include zero. This

Figure 2. The results of structural equation modeling



Note. **p < 0.05; **p < 0.01; ***p < 0.001.*

Table 6. Summary of mediation mechanism analysis

Type of effect	Path	Estimate	S.E.	Bootstrapping 5000 time 95% CI			
				Bias-corrected		Percentile	
				LLCI	ULCI	LLCI	ULCI
Total effect 1	-	–0.395	0.137	–0.687	–0.135	–0.691	–0.137
Direct effect1	Information quality → Algorithmic avoidance	–0.061	0.154	–0.350	0.256	–0.363	0.245
Indirect effect 1	Information quality → Perceived manipulation → Algorithmic avoidance	–0.334	0.123	–0.641	–0.139	–0.619	–0.129
Total effect 2	-	0.233	0.078	0.091	0.396	0.092	0.397
Direct effect2	Homogeneous recommendation → Algorithmic avoidance	–0.053	0.083	–0.201	0.076	–0.219	0.065
Indirect effect 2	Homogeneous recommendation → Perceived manipulation → Algorithmic avoidance	0.286	0.106	0.139	0.505	0.142	0.513
Total effect 3	-	–0.357	0.120	–0.561	–0.090	–0.559	–0.089
Direct effect3	Algorithmic transparency → Algorithmic avoidance	–0.237	0.135	–0.469	0.059	–0.461	0.069
Indirect effect 3	Algorithmic transparency → Perceived manipulation → Algorithmic avoidance	–0.120	0.076	–0.309	0.000	–0.301	0.007

suggests that perceived manipulation mediates the relationships between information quality and algorithmic avoidance, as well as between homogenization of recommendations and algorithmic avoidance. The indirect effects are –0.334 and 0.286, respectively, supporting hypotheses H8 and H9.

Further analysis shows that controlling for the mediating effects, the bias-corrected and percentile confidence intervals for the direct paths "information quality → algorithmic avoidance" and "homogeneous recommendation → algorithmic avoidance" include zero. This indicates that the direct effects of information quality and homogenization of recommendations on algorithmic avoidance are not significant and that perceived manipulation fully mediates these relationships.

In the path "algorithmic transparency → perceived manipulation → algorithmic avoidance," the mediating effect of perceived manipulation in the relationship between algorithmic transparency and algorithmic avoidance is marginally significant. Moreover, the direct impact of algorithmic transparency on algorithmic avoidance is not significant, supporting hypothesis H10 that perceived manipulation fully mediates the relationship between algorithmic transparency and algorithmic avoidance.

DISCUSSION

This paper uses information ecology theory and psychological reactance theory to investigate algorithmic avoidance behavior in intelligent recommendation systems. It examines how information quality, homogeneous recommendation, and algorithmic transparency influence users and explores the mediating role of perceived manipulation. The study found support for all hypotheses except H1 and H3. Information quality and homogeneous recommendation do not directly influence algorithmic avoidance; instead, they affect it indirectly through perceived manipulation. Perceived manipulation mediates the relationships between information quality, homogeneous recommendation, and algorithmic transparency with algorithmic avoidance. The specific conclusions are as follows.

Direct Impact of Algorithmic Transparency and Perceived Manipulation

Algorithmic transparency has a direct negative impact on users' algorithmic avoidance behavior in intelligent recommendation systems, while perceived manipulation has a direct positive influence on this behavior. This suggests that reducing users' perceived manipulation or enhancing algorithmic transparency can both help minimize algorithmic avoidance behavior among users. This finding aligns with the conclusions drawn by Barth et al. (2017) and Kim et al. (2010). Due to the lack of explanatory information during decision-making processes, intelligent recommendation algorithms often evoke discomfort and avoidance (Langer et al., 2018). The operational mechanisms of algorithmic recommendations are frequently challenging to comprehend, leading to a lack of trust among users and resulting in algorithmic avoidance (Logg et al., 2019). When users cannot understand the operational mechanisms of algorithmic recommendations and perceive platform practices related to personal data collection, usage, and management as opaque, they are more likely to engage in algorithmic avoidance. Algorithmic transparency can effectively alleviate anxiety arising from the "algorithm black box," thus reducing users' algorithmic avoidance. The perceived manipulation of users in intelligent recommendation systems significantly influences their intention to accept recommendations. When users perceive a loss of choice regarding information and passively receive algorithmic recommendations, especially when personalized recommendations involve coercive "values indoctrination," they experience intense perceived manipulation, leading to resistance towards algorithms.

Reducing Users' Perceived Manipulation to Address Algorithmic Avoidance

Information quality and homogeneous recommendation cannot directly influence algorithmic avoidance among users of intelligent recommendation systems; instead, their impact is mediated indirectly through perceived manipulation. Perceived manipulation serves as a complete mediator in the relationships between information quality and algorithmic avoidance, homogeneous recommendation and algorithmic avoidance, as well as algorithmic transparency and algorithmic avoidance. Improving information quality on intelligent recommendation platforms significantly reduces users' perceived manipulation ($\beta = -0.437$, $P < 0.001$), subsequently lowering algorithmic avoidance. Both information quality and information relevance (Dai et al., 2020; Jung, 2017) affect evasion behavior. When users browse intelligent recommendation information, they tend to be more concerned about issues such as irrelevant information, low-quality information, and information narrowing. High-quality information can stimulate positive cognitive and emotional responses in users (Lee, 2012), thereby reducing the generation of algorithmic avoidance.

The recommendation of homogenized content by intelligent recommendation systems significantly enhances users' perceived manipulation ($\beta = 0.400$, $P < 0.001$), consequently leading to algorithmic avoidance. Users engage with network information platforms or apps to browse information, clicking to view content aligned with their interests. Therefore, leveraging intelligent recommendation systems, information platforms recommend content based on user preferences to enhance click-through rates, improve user experience, and increase user engagement. However, personalized intelligent recommendations may impact users' regular information search and browsing processes, leading to information narrowing—characterized by a single type of information and high similarity among recommendations. Simultaneously, it may result in neglecting other information users are interested in but have not clicked on. This attempt to alter users' normal information browsing behavior can induce a sense of compulsion and of being manipulated, ultimately causing algorithmic avoidance and potentially leading users to abandon the platform.

Algorithmic transparency can significantly reduce users' perceived manipulation ($\beta = -0.172$, $P < 0.01$), thereby decreasing users' algorithmic avoidance in intelligent recommendation systems. The "inexplicability" of algorithmic recommendations, the intrusiveness of data collection processes, and the lack of transparency and accountability can generate a sense of exploitation among users (Puntoni et al., 2021). Algorithmic recommendations may pose a threat to users' ownership of personal data, challenging individual control. This may lead consumers to perceive infringements on their decision-making freedom and autonomy, inferring manipulative intentions regarding the recommended content (Walz & Deterding, 2015). Consequently, resistance psychology may emerge, resulting in algorithmic avoidance.

Theoretical Contributions

This paper, grounded in the theoretical framework of information ecology, explores the mechanisms of the interplay among information quality, homogeneous recommendation, algorithmic transparency, and algorithmic avoidance behavior of users in intelligent recommendation systems. It offers a novel explanatory framework for the study of algorithmic avoidance. Existing research predominantly focuses on algorithmic avoidance in the context of robotic algorithms and lacks an in-depth analysis of algorithmic avoidance from the perspective of information ecology. This paper systematically analyzes the impact mechanisms of users' algorithmic avoidance in intelligent recommendation systems, not only expanding the research context and intrinsic mechanisms of algorithmic avoidance but also enriching the application of information ecology theory in the study of user behavior in the field of intelligent recommendations.

Furthermore, this paper adopts a psychological resistance perspective to analyze the mediating role of perceived manipulation in the relationships among information quality, homogeneous recommendation, algorithmic transparency, and algorithmic avoidance of users in intelligent recommendation systems. It validates the role of psychological resistance in the generation mechanism of users' algorithmic avoidance in intelligent recommendation systems. From a psychological standpoint, it further reveals how information quality, homogeneous recommendation, and algorithmic transparency influence algorithmic avoidance. The paper emphasizes that perceived manipulation is a crucial psychological factor leading to users' algorithmic avoidance in intelligent recommendation systems, highlighting its significant theoretical value in mitigating the formation of algorithmic avoidance in the context of intelligent recommendations.

Implications for Practice

Perceived manipulation is a critical psychological factor that leads to users' algorithmic avoidance in intelligent recommendation systems. To enhance consumer engagement and increase content click-through rates, online information platforms commonly employ intelligent recommendation systems to deliver personalized content to consumers. However, existing personalized information recommendations often fail to garner long-term favor from consumers. Under the "information cocoon" effect caused by homogeneous recommendations, personalized content recommendations frequently trigger consumers' perceived manipulation, resulting in their avoidance of intelligent recommendation algorithms.

Homogeneous recommendation is a significant factor causing psychological resistance among consumers and significantly contributes to the generation of consumer algorithmic avoidance behavior. Therefore, in the pursuit of intelligent information recommendations, continual optimization of algorithms and methods for information delivery is essential to prevent the ongoing narrowing of recommended content. Utilizing diverse methods to document consumer preferences, promptly detecting shifts in consumer preferences, and optimizing interactive design methodologies to empower consumers with information choices are crucial steps to mitigate homogenized information dissemination. Additionally, stochastic algorithms could be integrated to unearth latent user demands, enhance serendipitous information encounters, and elevate the comprehensiveness of information, aiming to reduce users' perception of manipulation.

Simultaneously, enhancing intelligent recommendation systems' information quality and algorithmic transparency can significantly reduce users' perceived manipulation, thereby decreasing users' algorithmic avoidance in intelligent recommendation systems. Many intelligent recommendation platforms delegate content creation to users, relying solely on click-through rates to judge content quality. Under this mechanism, the information pushed to users often contains low-quality content. Additionally, many content creators repackage high-quality content from others as pseudo-original, leading to a significant amount of duplicated content in the information presented to users. This situation is more likely to evoke users' perceived manipulation, ultimately resulting in algorithmic avoidance. Therefore, intelligent recommendation platforms must strengthen the management of information content quality. Employing semi-manual review methods can enhance content quality and improve user experience.

Furthermore, intelligent recommendation platforms should regulate the collection, use, and storage of users' personal data during operation. Implementing transparent and publicly disclosed rules for collecting, using, and storing user personal data enhances algorithmic transparency, reducing users' perceived manipulation while using intelligent recommendation platforms and thereby preventing algorithmic avoidance behavior. The conclusions of this study can provide theoretical guidance and reference for the standardized and positive development of intelligent recommendation platforms.

Limitations and Future Research

The respondents in this research questionnaire survey were limited to users of Chinese intelligent recommendation platforms. The situation of users in intelligent recommendation systems in other countries may differ, as users from various countries and cultural environments may have different attitudes toward recommendation algorithms. Subsequent studies could compare the findings of this study with results from other contexts to understand variations in users' attitudes and behaviors toward algorithms in the domain of intelligent recommendations across diverse cultural and national environments.

Additionally, the sample data obtained in this study lacks representation from individuals 45 and over and includes a higher proportion of male participants. While users under 45 may constitute the primary demographic for utilizing intelligent recommendation apps in China, this could introduce certain limitations to the research findings. It is recommended that the scope of sample collection be broadened in future studies and that the potential impact of gender on users' algorithmic avoidance tendencies in intelligent recommendation systems be further examined.

CONCLUSION

This study, grounded in information ecology theory and adopting a perspective rooted in psychological resistance, investigates the mechanisms through which platform information quality, homogeneous recommendation, and algorithmic transparency influence users' algorithmic avoidance in intelligent recommendation systems. The research findings indicate that information quality and homogeneous recommendation do not directly affect algorithmic avoidance; instead, their impact is mediated by perceived manipulation, which plays a complete mediating role between information quality and algorithmic avoidance, as well as homogeneous recommendation and algorithmic avoidance. Furthermore, algorithmic transparency significantly negatively influences algorithmic avoidance and perceived manipulation marginally and significantly mediates the relationship between algorithmic transparency and algorithmic avoidance. Perceived manipulation emerges as a crucial psychological factor leading to users' algorithmic avoidance in intelligent recommendation systems. The outcomes of our study provide theoretical and practical insights to improve the operation and development of intelligent recommendation platforms.

AUTHOR NOTE

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ENDNOTES

[1] https://www.wenjuan.com/

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