The Influence of Algorithmic Personalization on Users' Algorithmic Resistance Behavior on Social Media Platforms

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Abstract. Although personalized algorithmic recommendation services on social media platforms have enhanced the efficiency of information searching, it has the potential to induce "information cocoons" and trigger users' algorithmic resistance behavior. Based on the S-S-O (Stressor-Strain-Outcome) theoretical framework, this study attempts to explain how perceived personalization (Stressor) influences algorithmic rebellion behavior (Outcome), a proactive algorithmic resistance behavior. Additionally, it takes information narrowing and psychological reactance (Strain) as mediating variables, and algorithmic literacy as a moderating variable. Empirical results from 192 high-educated young people indicate that perceived personalization positively predicts algorithmic rebellion behavior, information narrowing, and psychological reactance play partial mediating roles in the relationship between perceived personalization and algorithmic rebellion behavior, and algorithmic literacy plays a moderating role in the aforementioned relationship. Our study enriches the research content of algorithmic resistance behavior, extends the application of the S-S-O theoretical framework, and provides insights for optimization and governance of platform algorithms.

Keywords: personalized algorithmic recommendation; algorithmic resistance behavior; information narrowing; psychological reactance; algorithmic literacy; S-S-O theory

1 Introduction

With the popularization and penetration of social media platforms, personalized algorithmic recommendations have obviously reshaped the lifestyle of modern people. Although personalized algorithmic recommendations have contributed to meeting users' personalized needs and improving the efficiency of information search, they may trap users in the "information cocoons", leading to resistance emotions and behaviors towards personalized algorithms [1]. Therefore, users' algorithmic resistance behavior has gradually become a hot issue in current research.

Algorithmic resistance behavior refers to an important coping mechanism for users to resist the negative impacts brought by personalized algorithmic recommendations [1].

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Existing research on such behavior mainly focuses on two aspects: the behavioral strategies and the influencing factors. In terms of behavioral strategies, Siles et al. (2020) [2] believed that users usually adopted resistance or submission strategies when faced with homogeneous information provided by algorithm recommendation technologies; Kang & Lou (2022) [3] believed that users can create multiple accounts to train algorithms. With regard to influencing factors, Xie et al. (2022) [4] found that users' specific needs (such as voyeurism and escapism) significantly improved users' algorithm perception ability, thereby contributing to algorithmic resistance behavior. Zhang et al. (2024) [5] pointed out that information narrowing and information overload are the main factors causing users to generate algorithmic resistance and avoidance behaviors.

Although scholars have made significant contributions to the research of algorithmic resistance behavior, there are still some deficiencies. First, research on algorithmic resistance behavior in users' interactions with algorithmic recommendation systems is still in its infancy. Particularly, as a more proactive and high-interactive behavioral strategy, algorithmic rebellion behavior has received little attention in existing studies. Second, traditional technology acceptance model and Stimulus-Organism-Response (S-O-R) frameworks are commonly used for analyzing algorithmic resistance behavior. However, as an important environmental characteristic in social media, personalized algorithmic recommendation may be perceived as a stressor, which further leads to strain responses and outcomes. It is necessary to use S-S-O theoretical model to explore the antecedents of algorithmic resistance behaviors. Finally, the effect of perceived personalization may vary according to user characteristics [4]. Existing studies mostly focus on platforms or users separately, ignoring the complexity of interaction between algorithmic recommendation systems and users. Therefore, it is necessary to explore the boundary role of users' algorithmic literacy.

Based on the S-S-O model, our study intends to explore how the personalized personalization affects algorithmic rebellion behavior, and thus address the aforementioned limitations. This study takes information narrowing and psychological reactance as mediating variables, and users' algorithmic literacy as a moderating variable. By analyzing the data, this study would expand the influencing factors and boundary conditions of algorithmic resistance behavior, thereby providing feasible insights for subsequent algorithmic optimization on social media platforms.

2 Theoretical Model and Hypotheses

2.1 S-S-O theoretical model

The Stress-Strain-Outcome (S-S-O) theoretical model was first proposed by Gary and Randi [6] in 1993, initially used to explain the phenomenon of burnout at the workplace. It was later extended to explain the mechanisms of stress, and has been widely applied in fields like organization management and social media, such as the relationship between excessive use of social networking sites and poor academic performance [7], and the impact of emotional dysregulation on organizational citizenship behavior.

The S-S-O model centers on three key dimensions. Stressor, the initial stage of the model, refers to psychological or behavioral factors that can have adverse impacts on individuals. In this study, stressor is users' perceived personalization, which reflects the degree to which users perceive personalized algorithmic recommendations on social media. When the level of this stressor is high, it may stimulate users and lead to a sense of stress. Strain is the intermediate reaction resulting from the stressor, referring to the adverse states or changes in physical condition. In this study, the strain includes two dimensions: information narrowing and psychological reactance. Outcome is the final stage of the S-S-O model, representing the ultimate consequences that individuals experience under the sustained influence of strain. In this study, the outcome is users' algorithmic rebellion behavior. It suggests that when users are under continuous psychological pressure caused by perceived personalization, they will eventually adopt algorithmic rebellion behavior.

In addition, users' algorithmic literacy reflects their ability to understand algorithm and participate in algorithmic decision-making processes. It can help users comprehend the internal logic of algorithmic systems, recognize potential risks, and thus take effective measures to mitigate the adverse effects. This study takes users' algorithmic literacy as a moderating variable, which influences the effect of perceived personalization. The conceptual model of this study is shown in Fig. 1.

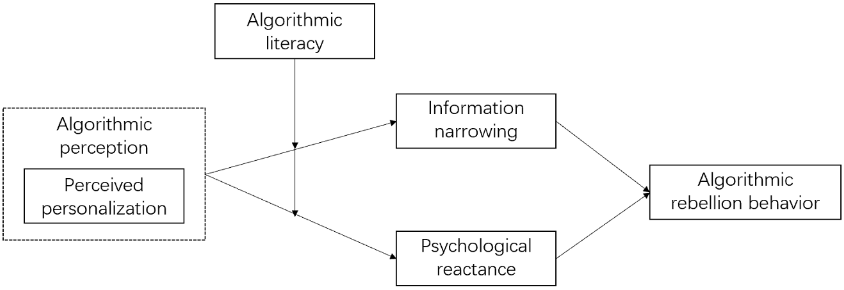

Fig. 1. Conceptual Model Diagram

2.2 Hypothesis

Perceived Personalization and Algorithmic Rebellion Behavior.

Algorithmic rebellion behavior, characterized by a high degree of subjective initiative, reflects the interactivity between users and algorithms. While users enjoy the convenience brought by personalized recommendations, they are concerned about the potential risks caught by personalization as the level of perceived personalization increases, such as privacy leakage. Therefore, users will actively interact with algorithmic systems to train platforms' recommendation algorithms, in an attempt to influence and adjust their recommendation methods to obtain a more diverse and rich information experience. Based on this, this study proposed the following hypothesis:

H1. The level of perceived personalization has a positive impact on algorithmic rebellion behavior.

The Mediating Role of Information Narrowing and Psychological Reactance.

In most cases, the effect of perceived personalization is based on users' past experiences and browsing history. As the level of perceived personalization increases, it creates "filter bubbles" in the information-seeking process, filtering out content that the system deems 'uninteresting' and thus isolating users from information outside their areas of interest, limiting their information breadth. At the cognitive level, such filter bubbles restrict the breadth and forward-looking nature of users' cognition, therefore exacerbating information narrowing.

Meanwhile, in order to alleviate the information homogeneity, or the 'information cocoon' effect, users will adopt proactive algorithmic resistance strategies such as expanding information sources or clicking on other types of information to maintain the diversity of information acquisition (Velkova and Kaun, 2021) [8]. Therefore, information narrowing can lead users to adopt algorithmic rebellion behavior. Based on this, this study proposed the following hypothesis:

H2a. The level of users' perceived personalization has a positive impact on information narrowing.

H2b. Information narrowing is positively correlated with algorithmic rebellion behavior.

H2c. Information narrowing partially mediates the relationship between the level of perceived personalization and algorithmic rebellion behavior.

The Moderating Effect of Users' Algorithmic Literacy.

Users' algorithmic literacy reflects their knowledge about personalized algorithmic recommendations, and may influence their understanding of recommended information on social media platforms. Users with high level of algorithmic literacy can recognize that the goal of such recommendations is to increase users' dwell time and click-through rates. This allows them to actively manage their usage behavior, broaden their information sources through interactions with the system, and significantly avoid the influences of 'filter bubbles'. Meanwhile, such users understand more about the logic and potential risks of algorithmic recommendations. Thus, users with high algorithmic literacy tend to maintain critical attitudes towards personalized algorithmic recommendations, thereby reducing the manipulative effects of the systems on their behavior.

In contrast, users with low algorithmic literacy may get immersed in prolonged viewing. Because the accuracy of recommended content mitigates the degree of their psychological reactance. Therefore, our study proposes:

H4a. Users' algorithmic literacy weakens the relationship between perceived personalization and information narrowing.

H4b. Users' algorithmic literacy weakens the relationship between perceived personalization and psychological reactance.

3 Methodology

3.1 Data and Sample Collection

This study adopts questionnaire survey to collect data. The questionnaire was designed based on mature scales from existing literature, and adjusted according to Chinese context. It was developed through strictly translation and back-translation, and then revised based on respondents' feedback.

The survey data were collected through Wenjuanxing, an online survey platform among social media (e.g., Douyin) users in China. College students were recruited for this research. This study first randomly distributed 200 users, and 196 ultimately participated in this survey. After excluding invalid data owing to inactive users and long response times, 192 valid questionnaires were obtained, with a recovery rate of 96%.

The demographic characteristics of the survey sample are as follows: females accounted for the majority of respondents (71.4%), the age of respondents was concentrated in the 18-22 age group (52.6%), the educational level of respondents was concentrated at the bachelor's degree level (67.4%), and 73.3% of respondents had been using social media for more than 5 years.

3.2 Variable Measurement

The scales used in this study are all derived from mature scales used in related studies, with appropriate modifications made in combination with the research of this study. 5-point Likert-type scales were used to measure each item from (1) "Strongly disagree" to (5) "Strongly agree".

1. Perceived Personalization (α=0.850, AVE=0.777). Referencing to the research of Li's (2016) [9], it is measured by 3 items.
2. Information Narrowing (α=0.768, AVE=0.685). Based on Sunstein's (2001) [10] study, it is measured through 3 items.
3. Psychological Reactance (α=0.851, AVE=0.771). Referencing to the study of Bleier and Eisenbeiss's (2015) [11], it is measured by 3 items.
4. Algorithmic Literacy (α=0.788, AVE=0.711). It is measured with 4 items adopted from Zarouali et al.'s (2021) [12] and Dogruel et al.'s (2022) [13].
5. Algorithmic Literacy (α=0.788, AVE=0.711). It is measured with 4 items adopted from Zarouali et al.'s (2021) [12] and Dogruel et al.'s (2022) [13].
6. Control Variables. Education level, age, and social media platform usage experience are selected as control variables.

3.3 Reliability, Validity Testing and Factor Analysis

Table 1 lists the descriptive analysis results of each variable. It shows that the correlation coefficients between any two variables are less than 0.650, except for that between information narrowing and psychological reactance. Therefore, the possibility of multicollinearity is relatively small. The maximum value of VIF is 1.508, which is less than 2, further confirming that the threat of multicollinearity is small.

The α values of all indicators are greater than 0.757, indicating good reliability; Next, the indicator convergent validity was good because the factor loadings range from 0.675 to 0.908; Last, the correlations between constructs are smaller than the square root of AVE for each construct, confirming good discriminant validity.

Table 1. Descriptive Analysis Results

Variable	Mean	Standard Deviation	1	2	3	4	5	6	7	8
1.Education Level	2.063	0.575	N/A							
2.Age	2.714	0.896	-0.056	N/A						
3.Usage Experience	3.625	0.683	0.113	0.055	N/A					
4.Perceived Personalization	3.870	0.790	-0.036	-0.161*	0.297***	0.882				
5.Information Narrowing	3.767	0.807	-0.017	-0.148*	0.231**	0.541***	0.878			
6.Psychological Reactance	3.429	0.894	-0.052	-0.057	0.122	0.330***	0.664***	0.843		
7.Algorithmic Literacy	3.830	0.758	0.049	-.0036	0.234**	0.463***	0.538***	0.537***	0.843	
8.Algorithmic Rebellion Behavior	3.495	0.845	-0.007	-0.109	0.115	0.398***	0.531***	0.626***	0.556**	0.822

Note: *, **, *** represent $p<0.05$, $p<0.01$, $p<0.001$ respectively; bold numbers on the diagonal are the square roots of AVE; N/A indicates unsuitable for analysis

3.4 Data Analysis and Results

This study uses multiple linear regression to test the theoretical hypotheses proposed. Accoding to stepwise regression method, the testing models are obtained through following steps. (1) All control variables were added to control their influence on the dependent variable; (2) The independent variable were added on the previous step; (3) The mediating variables, such as information narrowing and psychological reactance were added to test their mediating effects of the mediating variables. The regression results are shown in Table 2.

Table 2. Regression Results

Variable	Algorithmic Rebellion Behavior				Information Narrowing			Psychological Reactance		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Perceived Personalization		0.417***	0.176*	0.228**		0.513***	0.322***		0.359***	0.092
Information Narrowing			0.470***							
Psychological Reactance				0.526***						
Algorithmic Literacy							0.380***			0.581***
Algorithmic Literacy* Personalization							-0.054+			-0.037
Education Level	-0.040	0.007	0.016	0.044	-0.076	-0.019	-0.046	-0.111	-0.071	-0.112
Age	-0.111	-0.043	-0.013	-0.038	-0.148*	-0.065	-0.088	-0.068	-0.010	-0.035
Usage Experience	0.154+	0.001	-0.047	-0.022	0.290**	0.102	0.033	0.175+	0.044	-0.037
Cons	3.321***	1.981***	1.217***	0.900*	3.275***	1.626***	1.301***	3.208***	2.055***	1.325**
R2	0.027	0.160	0.301	0.436	0.082	0.303	0.417	0.024	0.112	0.307
Adj R2	0.012	0.142	0.282	0.421	0.067	0.288	0.398	0.008	0.193	0.284
F value	1.756	8.925	16.017	28.778	5.601**	20.316***	22.014***	1.537	5.886***	13.653***

Note: +, *, **, *** respectively indicate $p<0.1$, $p<0.05$, $p<0.01$, $p<0.001$.

Model 2 shows that the regression coefficient between perceived personalization and algorithmic rebellion behavior is significantly positive (β=0.417, P<0.001), indicating a positive correlation between them, and H1 is supported. Model 6 indicates that the degree of perceived personalization has a significant positive impact on information narrowing (β=0.513, P<0.001), verifying H2a. Model 3 shows that information narrowing has a significant positive impact on algorithmic rebellion behavior (β=0.470, P<0.001), verifying H2b. Compared with Model 2, the coefficient of perceived personalization in Model 3 decreases but remains significant (β=0.176, P<0.05). Therefore, information narrowing has a partial mediating effect between perceived personalization and algorithmic rebellion behavior, supporting H2c. Similarly, Model 9 shows that the degree of perceived personalization has a significant positive impact on psychological reactance (β=0.359, P<0.01), verifying H3a; Model 4 shows that psychological reactance has a significant positive impact on algorithmic rebellion behavior (β=0.526, P<0.001), verifying H3b; and compared with Model 2, the coefficient of perceived personalization decreases but remains significant (β=0.228, P<0.01). Thus, psychological reactance also plays a partial mediating role between perceived personalization and algorithmic rebellion behavior, supporting H3c.

To further test the moderating effect of users' algorithmic literacy, this study first mean-centered algorithmic literacy and perceived personalization, and then run Model 7 and Model 10, respectively. Model 7 shows that the coefficient of the interaction term between perceived personalization and algorithmic literacy is significantly negative ($\beta=-0.054$, $P<0.1$), indicating that algorithmic literacy weakens the relationship between perceived personalization and information narrowing, supporting H4a. Model 10 shows that the coefficient of the interaction term between perceived personalization and algorithmic literacy is negative but not significant ($\beta=-0.037$, $P>.1$), suggesting that algorithmic literacy does not play a moderating role in the relationship between perceived personalization and psychological reactance, so H4b is not supported. The reason may be that psychological reactance is influenced by various factors, such as emotional state, environment, and personal interests, which may all affect the moderating effect of algorithmic literacy.

To more intuitively understand the moderating effect of users' algorithmic literacy, this study draws the corresponding moderation diagram based on Model 7 (Fig. 2). As shown in Fig. 2, when the level of users' algorithmic literacy increases, the effect of perceived personalization on information narrowing is weakened. Therefore, H4a is further confirmed.

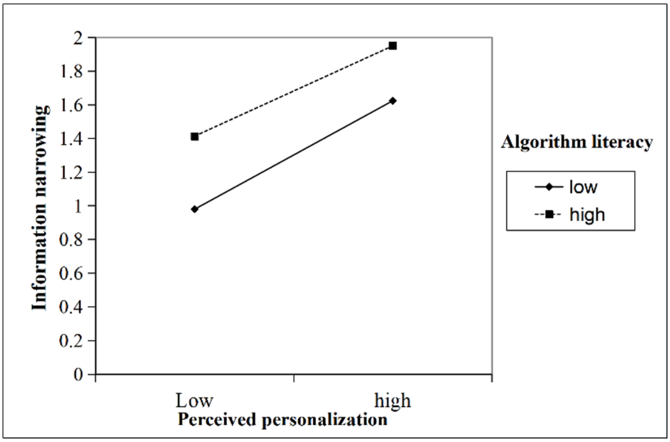

Fig. 2. The moderating effect of user algorithm literacy

4 Discussion and Conclusion

4.1 Research Conclusions

Based on the S-S-O theoretical framework, this study examined the impact of users' perceived personalization on algorithmic rebellion behaviors. It takes information narrowing and psychological reactance as mediating variables and algorithmic literacy as a moderating variable. The research conclusions are as follows:

First, perceived personalization of algorithmic recommendations positively influences users' algorithmic rebellion behavior. Specifically, the more personalized the recommendations, the more aligned they are with users' preferences. Although users enjoy the convenience of personalized recommendations, they are concerned about potential risks caused by them, such as privacy leakage. Consequently, users will actively interact with algorithmic systems to try to adjust its recommendation methods, thereby increasing algorithmic rebellion behavior.

Second, information narrowing and psychological reactance respectively play mediating roles between perceived personalization and algorithmic rebellion behaviors. On the one hand, from the perspective of information content, personalized algorithmic recommendations generate "filter bubbles" that isolate users from information outside their interest areas. This limits users' information breadth and foresight, thereby exacerbating information narrowing. From an emotional perspective, the increased use of such services leads users to generate negative emotions, such as feeling monitored or manipulated, resulting in privacy concerns. These concerns, which are the strains in the S-S-O model, intensify psychological reactance in turn. Ma et al. (2022) [14] reached similar conclusions. To alleviate these strains, users may adopt algorithmic rebellion strategies to maintain their freedom to acquire information.

Finally, algorithmic literacy negatively moderates the relationship between perceived personalization and information narrowing. Users with high algorithmic literacy are more aware of the underlying logic and potential risks of personalized algorithmic recommendations. They understand that, although they enjoy the convenience of algorithms, they must also consider the risks of privacy leakage and cognitive dissonance. Thus, such users often have a critical attitude toward personalized recommendations. Nevertheless, the moderating effect of algorithmic literacy is insignificant in the model of perceived personalization and psychological reactance. One reason for this phenomenon is that users' psychological reactance is strongly subjective and easily influenced by factors such as emotional states, external environments, and changes in personal preferences. These factors may affect the moderating role of algorithmic literacy.

4.2 Theoretical Contributions

First, this study enriches the research on the factors and mechanisms that influence algorithmic resistance behavior. Current research on this behavior is still in its infancy. Research on highly interactive algorithmic rebellion behavior is especially scarce. Little attention has been paid to the factors influencing algorithmic rebellion behavior in the context of personalized recommendation environments [5]. This study begins with users' perceived personalization of algorithms, uses questionnaires and quantitative analysis methods to deeply explore its impact on algorithmic rebellion behavior and the underlying mechanisms, and examines the conditions and degrees to which different variables influence it. Our study contributes to the literature on algorithmic resistance behavior among users of personalized algorithmic recommendations on social media platforms. It provides novel findings on the interaction between users and algorithm systems and fills a theoretical gap in the study of algorithmic rebellion behavior.

Second, this study uses the S-S-O theoretical framework to construct a model of algorithmic rebellion behavior on social media platforms. This expands the situational application scope of the S-S-O model. Most existing research relies on traditional technology acceptance models and the S-O-R theoretical framework for analysis. Personalized algorithmic recommendations, as an environmental characteristic of social media, may be perceived by users as stressors, leading to stress responses. Therefore, it is necessary to adopt the S-S-O model for research. This study considers users' perception of algorithms, or perceived personalization, as the stressor; information narrowing and psychological reactance as the strains; and algorithmic rebellion behavior as the outcome. The results demonstrate that the effect of perceived personalization on algorithmic rebellion behavior follows the 'stressor-strain-outcome' path mechanism. This mechanism responds to and extends existing literature on the relationship between psychological reactance, information narrowing, and algorithmic rebellion behavior. Thus, this study extends the SSO theoretical framework to the domain of algorithmic resistance behavior, thereby further enriches the SSO theoretical system.

Finally, this study reveals the underlying mechanisms of how perceived personalization influences users' algorithmic rebellion behavior. It also enriches the research literature on algorithmic resistance behavior by exploring the boundary conditions of such behavior. By taking information narrowing at the informational level and psychological reactance at the emotional level as mediating variables, our study reveals how perceived personalization influences algorithmic rebellion behavior. This provides a new perspective on researching the intrinsic mechanisms of algorithmic resistance behavior. Furthermore, by introducing the moderating role of users' algorithmic literacy and considering the impact of the interaction between algorithmic systems and users, our study confirms the boundary effect of algorithmic literacy. Thus, this study broadens the scope of research on algorithmic rebellion behavior and its boundary conditions, providing deeper insights for the subsequent optimization of algorithms and improvement of algorithm governance on social media platforms.

4.3 Practical Implications

This study has several practical implications. First, social media platforms should optimize their personalized algorithmic recommendations and avoid the 'personalization = information narrowing' dilemma. Personalized algorithmic recommendations are based on the idea that platforms predict user preferences through user behavior data in order to efficiently match content with users. The core lies in efficiency rather than singularity. A common defect in current algorithmic systems is that they simplify flexible, efficient content into singular content. Thus, social media platforms must focus on data-driven prediction of user preferences, create accurate user portraits, enhance the efficiency and flexibility of content recommendations, and achieve efficient matching between content and users. This will help them avoid the 'information cocoon' dilemma.

Second, platforms should establish flexible and diverse mechanisms for user to feedback on emotions to alleviate negative emotions caused by algorithmic recommendations. Most of current algorithmic logic center on click-through rates and dwell time; platforms often overemphasize user behavioral data while neglecting users' emotional experiences while consuming content. To address this, platforms should add lightweight, multidimensional emotion feedback options, such as "like" and "not interested". They should also introduce emotion labels, such as "causes anxiety", "uncomfortable content", "extreme viewpoints", and "overly oppressive". These options allow users to directly express their feelings about the content instead of indirectly expressing them through passive actions like swiping away or closing. By combining these labels with specific user behavioral data, algorithmic systems can proactively recommend content of different styles and domains, thereby mitigating negative experiences.

Finally, social media platforms should strengthen the governance model of personalized algorithmic recommendation systems with a focus on technical compliance and value guidance. Based on compliance with laws and regulations, they should optimize algorithmic functions, improve review processes, and increase transparency. They can safeguard users' right to know and choice by providing functions such as open personalized adjustment, emotional feedback, and recommendation shutdown. Additionally, platforms should strengthen personal privacy protection, standardize the process of collecting user behavior data, and maintain a clear and healthy online ecosystem and public social interests while improving content matching efficiency. This will help to achieve balanced development between technological innovation and social responsibility.

4.4 Research Deficiencies and Prospects

Our study still has some limitations. First, the sample size was relatively small (the planned sample size was 200, but only 192 were valid ultimately). The respondents' characteristics were relatively concentrated, mainly consisting of young people with higher education backgrounds. Therefore, the research results may be insufficiently generalizable. Future studies can address this shortcoming by collecting more comprehensive and objective data samples from multiple platforms using online and offline methods.

Second, some variables in the model reflect high interactivity between users and algorithmic systems, such as perceived personalization and psychological reactance. These variables have strong subjective initiative and may be influenced by multiple external factors. The actual situation in real-life scenarios may be more complex. Constrained by research conditions, our study's model only introduced algorithmic literacy as a moderating variable, and it is insufficient to fully cover all scenarios of algorithmic rebellion behavior in real contexts. To gain a more comprehensive understanding of users' algorithmic rebellion behavior, future research can further extend to other scenarios, deeply explore the mechanisms of other variables acting on algorithmic rebellion behavior, thereby expanding broader theoretical applicability scenarios.

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