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Unravelling the Algorithm Manipulation Behavior of Social Media Users: A Configurational Perspective

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ABSTRACT

Despite the potential benefits brought by algorithm recommendation, it also causes some disadvantages such as information cocoon. As a countermeasure, social media users may manipulate algorithm to meet their needs. However, prior studies on algorithm manipulation are either qualitative or focus on net effects without considering joint effects. Thus, this study theorizes and empirically tests a configurational model of algorithm manipulation by considering the effects of personality (i.e., openness), information quality (e.g., information narrowing and information redundancy), and algorithm quality (e.g., algorithm fairness, accountability, and transparency). The fuzzy-set qualitative comparative analysis (fsQCA) based on survey data confirms our hypotheses.

Keywords: Social media, algorithm manipulation, algorithm quality, information quality, fuzzy set qualitative comparative analysis.

INTRODUCTION

With the development of personalized recommendation of social media, more and more users are immersed in the personal space constructed by algorithm recommendation. In China, Redbook, Tiktok, Bilibili and other shared social media are popular among young people. However, with the use of algorithm recommendation system, problems about algorithm awareness, value ethics and prejudice discrimination are also emerging. Due to the black box of the algorithm system, most ordinary users try to obtain the information they want through algorithm manipulation. Reports indicate that people have become aware of how algorithms shape various aspects of their lives while using social media and have begun actively manipulating algorithm to improve the quality of information service (Greenblatt, 2024).

Despite the practical importance of users' algorithm manipulation behaviors, the theoretical discussion on this issue is still in its infancy. Specially, current research on algorithm manipulation behavior mainly focuses on the resistance manipulation behavior but neglects the cooperative manipulation behavior. Karizat et al. (2021) explored how Tiktok users understand the algorithm system and the behavioral strategies adopted to resist the algorithm's filtering of personal identity and the threat to algorithm sovereignty. Moreover, scholars have explored the ways of social media user resistance algorithm on Facebook, which includes two daily resistant tactics (Van der Nagel, 2018). However, users may not only passively react to algorithm recommendation through resistance but also actively leverage the algorithm to satisfy their information needs through cooperation. Thus, this study tries to distinguish two kinds of algorithm manipulation namely resistant manipulation and cooperative manipulation and explore their differential mechanisms.

Further, most of prior studies on social media users' algorithm manipulation are exploratory and qualitative, lacking the theorydriven confirmative investigation. Prior studies on algorithm manipulation have been majorly conceptual by identifying the key concepts and processes associated with algorithm manipulation or qualitative through interviews and case studies (Simpson & Semaan, 2021). Although these studies provide some initial insights on the issue, the causal mechanisms of two types of algorithmic manipulation have not been unraveled, and whether the findings based on case studies can be generalized is still unknown. Thus, this study aims to theorize the underlying mechanisms and empirically test these mechanisms through a quantitative study.

Finally, past research based on the variance perspective has explored the additive or net effects of a variety of factors but failed to comprehensively consider their combined effects from a configurational perspective. Shin (2020) proposed an experience model of news recommendation algorithm based on the technical characteristics of the algorithm to explore the interactive practice process between users and algorithms. Furthermore, the effect of individual differences on users' algorithm manipulation behavior has been overlooked. The differences in users' personal traits will lead to certain cognitive differences, differences in the perception of information and algorithms, and also affect their behavioral tendencies. Under the combined effect of three key factors concluding individuals, information and algorithm, the conditions under which users engage in cooperative or resistant algorithm behavior are not singular. Therefore, we need to consider the causal mechanisms of user algorithm manipulation behavior from a configurational perspective.

To fill the above research gaps, this study tries to explore the differential configurations of a set of causal conditions resulting in resistant and cooperative algorithm manipulation behavior. Specifically, these causal conditions cover three aspects, e.g., information quality and algorithm quality of social media and users' personal traits (openness in particular). This study contributes to the existing literature in several ways. Firstly, this paper categorizes users' algorithm manipulation behavior into cooperative and resistant types based on the interaction relationship between users and algorithms. Secondly, this study addresses individual differences in adopting algorithm manipulation behavior and explores how users with varying levels of openness differ in forming these behaviors. Finally, the study explores how information quality (including information narrowing and information redundancy) and algorithm quality (including fairness, accountability, and transparency) jointly determine users' algorithm manipulation behaviors.

LITERATURE REVIEW

Algorithm Manipulation Behavior of Social Media Users

Research indicates people try to understand algorithms through their own identities (Karizat et al., 2021). Users' identities on platforms include personal and social identities, reflecting characteristics such as personal interests and group affiliations. User interaction with algorithms on social media is based on their desires for algorithms to better match their personal preferences after training. On the one hand, users voluntarily disclose their self-preferences to the algorithm system to get a better "for you page." On the other hand, when users are dissatisfied with the information services provided by algorithms, they will take a series of proactive resistance actions to disrupt the algorithm system (Simpson & Semaan, 2021).

As the negative impacts of algorithms have increasingly become a research focus, the subjectivity of users as algorithm users has started to be captured. When users experience negative emotions such as fatigue or distrust towards algorithms, how they negotiate with algorithms to "re-domesticate" or resist them has become a trend and frontier in research. In studies on the interaction practices between users and algorithms, scholars have focused on the generation of users' resistance behavior and intentions towards algorithms, as well as the strategies they adopt for resistance. Karizat et al. (2021) used interviews to explore how TikTok users understand algorithm systems and the behavioral strategies they adopt to resist the filtering of their personal identities and threats to algorithmic sovereignty. Simpson et al. (2021) conducted interviews with marginalized social groups on TikTok, specifically the LGBT community, to uncover their counter-strategies against algorithmic suppression of their expression.

Based on the research perspective of scholars such as Zhao et al.(2022), we categorize the relationship between users and algorithms into cooperative and resistant types. Algorithm manipulation encompasses behavior where users seek to gain sovereignty and actively participate in altering the algorithm's output. Cooperative manipulation refers to users proactively utilizing algorithm rules to change input values to obtain more satisfactory output results. In contrast, resistant manipulation involves users refusing to cooperate with algorithm rules, directly resisting the algorithm, such as by shutting down the algorithm system or deliberately disrupting it.

Big Five Personality Theory

The Big Five personality theory is a psychological framework describing personality traits, dividing human personality into five dimensions: agreeableness, conscientiousness, extraversion, neuroticism, and openness (Costa & McCrae, 1999). Agreeableness refers to an individual's friendliness and cooperativeness; conscientiousness to being organized and planned; extraversion to being outgoing and energetic; neuroticism to anxiety and emotional instability; and openness to being receptive to new experiences, ideas, and perspectives. This theory describes psychological individual differences and is widely used in user experience and behavior research, which demonstrates the close relationship between the Big Five personality theory and individual cognition and behavior.

Algorithm is a new technical product in the Internet era, so the process of algorithm manipulation behavior is closely linked to individuals' perception and exploration of novel phenomena. Therefore, compared to the other four personality traits, which describe individuals' friendliness and sociability, emotional stability, and sense of responsibility, openness has a stronger connection with the occurrence of user algorithm manipulation behavior. As one of the Big Five traits, openness describes a person's desire for adventure and need for diversity. Openness is often associated with how individuals behave in their environment, with such personalities exhibiting a more positive and open mindset when facing external stimuli. Research indicates that individuals with high openness have active cognition and a stronger willingness to participate in daily activities (Chen et al., 2022). These individuals are driven by curiosity to explore new things and are more willing to interact when browsing information on social media, such as liking, commenting, and sharing (Lee et al., 2014). The higher the user's openness, the stronger their willingness to explore new things and their ability to accept new experiences. This influences their interaction with algorithms, suggesting that high openness is a significant factor in algorithm manipulation behavior.

Information Cocoon Theory

The concept of the information cocoon was proposed by Cass Sunstein. It refers to a situation in personalized information services where users tend to access information based on their personal preferences (Sunstein, 2006). Over time, users become trapped in an information cocoon that aligns with their own views, ignoring other information. Research indicates that the information cocoon effect limits individuals' exposure to diverse information, leading to information that is homogeneous and limited in scope.

The quality of information on social media directly affects users' value assessment of content, which in turn affects their preference and emotional experience. The information cocoon effect is often accompanied by the creation of filter bubbles, which can lead to cognitive biases, amplify individual emotions, and consequently affect user decisions (Dahlgren, 2020). Social media users' personal preferences lead to a convergence in their information choices, resulting in higher similarity and redundancy in the content they focus on. Popular content tends to be limited and narrowed. The information cocoon, as a manifestation of information narrowing and redundancy, is often related to users' emotional experiences and negative psychology. Information narrowing refers to the decreasing exposure of users to information excluded by the recommended algorithm, leading to a decrease in the diversity and depth of the information they receive (Huang et al., 2020); information redundancy refers to the problem of information repetition in the series of information users encounter (Zhang et al., 2002). When the information horizon on social media narrows, users' needs for diversity and novelty in information are not met, leading to feelings of fatigue towards social media (Karapanos et al., 2016), which in turn affects their behavior in using algorithms.

The FAT Framework of Algorithm

The algorithm acceptability model, developed from affordance theory and technology acceptance theory, evaluates algorithm systems across three dimensions: Fairness, Accountability, and Transparency—collectively known as the FAT framework. The FAT framework is often associated with research on users' technological acceptance and adoption of algorithms (Shin, 2020), providing a theoretical perspective for explaining behavior and cognitive decision-making in user-algorithm interactions. Algorithm fairness means that the decisions of the algorithm should not lead to discriminatory or unfair outcomes (Lee, 2018); algorithm accountability emphasizes the responsibility of the developers and designers of the algorithm for its impact or consequences on society (Shah, 2018); algorithm transparency refers to the disclosure of information about how the algorithm drives various computing systems, involving sensitive data and the potential consequences of the system's implicit acquisition of user knowledge (Diakopoulos & Koliska, 2017).

Unlike the information dimension, the design rules of the algorithm system are related to the quality of the algorithm's service, and users' perception of the quality of the algorithm may affect their trust and satisfaction with its use. While algorithmic technology brings convenience to individuals, users also perceive issues regarding fairness and accountability. Research shows that when users experience discrimination from algorithms based on their identity (such as race, appearance, or social status) while using social media, they develop feelings of rejection and distrust towards the algorithms (Karizat et al., 2021). Accountability can provide users with responsibility assurances regarding the algorithm's structure, function, and recommendations, and highly accountable platforms enhance users' control and trust in the algorithm. Transparency allows users to understand the logic behind algorithm better meet user needs. In the context of social media platforms, the fairness, accountability, and transparency of algorithms are crucial factors in building user trust and increasing user engagement. Therefore, the technical characteristics of algorithms significantly influence users' algorithm manipulation behavior on social media.

RESEARCH MODEL AND HYPOTHESES

Our research constructs a user algorithm manipulation model based on three dimensions: user personal characteristics, information quality, and algorithm quality. The model explains how individual, information, and algorithm factors interact to influence social media users' algorithm manipulation behavior.

0 1		1	High resistant algorithm manipulation	Low resistant algorithm manipulation	
H1a	H1b	H1c	H2a	H2b	H2c
•	•	\otimes	•	•	\otimes
			•	\otimes	
•	\otimes				
	orithm manipulation H1a •	orithm manipulation algorithm in algorithm in algorithm in the second se	Description algorithm manipulation H1a H1b H1b H1c • • • •	High cooperative Low cooperative algorithm prithm manipulation algorithm manipulation manipulation H1a H1b H1c H2a • • • • • •	High cooperativeLow cooperativealgorithmalgorithmorithm manipulationalgorithm manipulationmanipulationmanipulationH1aH1bH1cH2aH2b \bullet \odot \odot \bullet \odot

the user's perception of these two dimensions, the lower the information quality. Algorithm quality includes three dimensions: algorithm fairness, accountability, and transparency. The stronger the user's perception of these three dimensions, the higher the algorithm quality. \bullet indicates the core condition is present; \otimes indicates the core condition is absent.

As shown in Table 1, at the level of user personal characteristics, we consider high openness as a reflection of the user's main consciousness in the interaction process with the algorithm, leading to algorithm manipulation behavior. In terms of algorithm quality and information quality dimensions, users' cooperative manipulation is mainly influenced by the algorithm quality of social media, while their resistant manipulation is primarily influenced by the quality of information they encounter.

Cooperative Algorithm Manipulation

Research has shown that people tend to use trustworthy systems (Rai, 2020). When the content recommended by algorithms is more accurate, free from bias and discrimination, the content moderation of social media and the developers of algorithms can be held accountable for the technology they provide, and the operational logic of the algorithm system is more transparent, users' trust in using the platform is enhanced (Liu & Wei, 2021). In a positive environment, the cognitive evaluation of social media algorithm systems is also more positive (Lazarus & Folkman, 1984), leading to a higher level of cooperative algorithm manipulation. For users with openness, their exploration of social media usage will be more active in order to obtain a better experience with diverse information and novel content services. When users encounter videos they like, they will repeatedly watch and share them to make their preferences clearer to the algorithm (Karizat et al., 2021), indicating a strong willingness to cooperate with the algorithm. When users feel the narrowing and redundancy of information, relying on trust in the technical system, individuals with openness will actively seek solutions to alleviate the trouble caused by information repetition, including actively selecting "not interested" to reduce similar recommendations. In other words, users will actively use algorithm rules to achieve their manipulation goals. On this basis, we propose that:

H1a: When algorithm quality (fairness, accountability, transparency) and user openness are present, regardless of the presence of information quality (information narrowing, information redundancy), social media users' cooperative algorithm manipulation will be high.

When users with openness perceive algorithmic bias and the accountability of the social media platform is low, and the problems encountered by users are difficult to be addressed and solved by relevant personnel, and the operational mechanisms of the algorithm system regarding the use of personal data are not transparent, negative environmental stimuli make users more prone to perceive risks (Ma et al., 2021), reduce trust in the platform, thus their willingness to cooperate in algorithm manipulation is low regardless of the quality of their information experience. Furthermore, when users lack openness, their acceptance and tolerance of new things are low, and their willingness to explore the use of social media algorithms is low (Chen et al., 2022). Therefore, the subjective consciousness of actively changing the algorithm input values to obtain desired results is weak, and they are passive in using social media, leading to a low level of cooperation with algorithms. Therefore, we put forward that:

H1b: When algorithm quality (fairness, accountability, transparency) is absent and user openness is present, regardless of the presence of information quality (information narrowing, information redundancy), social media users' cooperative algorithm manipulation will be low.

H1c: When user openness is absent, regardless of the presence of information quality (information narrowing, information redundancy) and algorithm quality (fairness, accountability, transparency), social media users' cooperative algorithm manipulation will be low.

Resistant Algorithm Manipulation

In the study of social media users' negative emotional experiences, information quality has a strong impact on user behavior. When the information quality of social media is poor, users with openness will resist homogeneous and redundant information environments, leading to negative emotions such as fatigue (Karizat et al., 2021). The system's recommendation often fail to keep up with changes in user demands, and similar information content will trigger negative evaluations of social media (Salo et al., 2020), leading to a resistance to algorithms. When the algorithm system are good, users with openness have the subjectivity of algorithm users and will actively explore methods to block algorithms to escape feelings of boredom, such as turning off application permissions for data blocking (Simpson & Semaan, 2021). When the algorithm system has problems such as algorithmic discrimination and other issues, the narrowing and redundancy caused by information cocoons will be difficult to regulate, and users will feel fatigue and powerlessness in using social media (Huang et al., 2023). So, the openness of individuals will have a higher intention to resist algorithms, thus resulting in resistant algorithm manipulation behavior. Based on this, we propose that:

H2a: When information quality (information narrowing, information redundancy) and user openness are present, regardless of the presence of algorithm quality (fairness, accountability, transparency), social media users' resistant algorithm manipulation will be high.

When users perceive high information quality in using social media, the information service is good, individuals with openness can continuously discover interesting and useful information based on their preferences. The depth and breadth of information are high, and users' cognitive functions do not feel overloaded or strained when processing information. So they have a strong sense of immersion in using social media, with lower levels of fatigue, irritability, and negative emotions (Soroya et al., 2021). Users' demands on social media are met, and their willingness for resistant algorithm manipulation is low. In addition, when users do not have the trait of openness, their lower demand for diversity makes them less sensitive to information narrowing and information redundancy on social media (Lee et al., 2014), and their awareness of actively exploring resisting algorithms to escape corresponding situations is weak, leading to a weaker resistance to algorithms. Thus, we posit that:

H2b: When information quality (information narrowing, information redundancy) is absent and user openness is present, regardless of the presence of algorithm quality (fairness, accountability, transparency), social media users' resistant algorithm

manipulation will be low.

H2c: When user openness is absent, regardless of the presence of information quality (information narrowing, information redundancy) and algorithm quality (fairness, accountability, transparency), social media users' resistant algorithm manipulation will be low.

User Algorithm Manipulation Behavior Quadrant

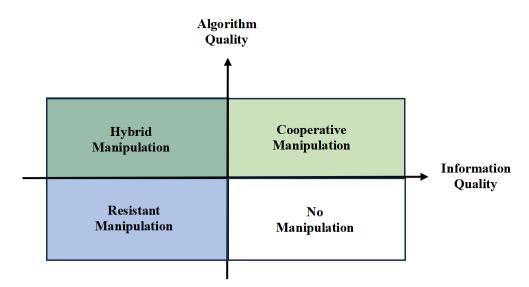


Figure 1: A typology of algorithm manipulation behaviors.

Due to the fact that the information dimension primarily focuses on how users engage with and process information, reflecting their preferences and emotional experiences, while the algorithm dimension emphasizes the design and operational mechanisms of algorithms, which influence users' decision-making and trust in the algorithms, this study categorizes the algorithmic manipulation behaviors of individuals with an open disposition based on these two dimensions. Therefore, based on the above analysis, this paper constructs a quadrant diagram of high-level user algorithm manipulation behavior with information quality and algorithm quality as the horizontal and vertical axes, respectively, as shown in Figure 1. Specifically, for users with high openness, when the algorithm system is reliable, and the information users receive on social media aligns well with their expectations, providing a good experience in terms of diversity and novelty, users will continue to use social media. They will interact cooperatively with the algorithm by liking, commenting, and allowing the algorithm to capture more personal preferences, feeding back the expected information to the users. This leads to high cooperative manipulation strategies. However, when the social media algorithm is good but the information is repetitive and homogeneous, on the one hand, users trust the algorithm system and actively click on uninteresting homogeneous information or like and search for diverse content to tame the algorithm to better match their recommendation expectations (Simpson & Semaan, 2021). On the other hand, this can also lead to user fatigue (Huang et al., 2023) and other negative emotions, prompting users to explore ways to block the algorithm, disrupt its accuracy in capturing personal preferences, and prevent them from being trapped in information cocoons, which represents resistance manipulation from the source of algorithm settings. In this situation, users will take mixed manipulation strategies, including cooperation and resistance. Moreover, when users perceive low breadth and depth of information, with severe information homogenization, and simultaneously have low acceptance and trust in the algorithm system, this situation triggers user resistance to using the algorithm. Such behavior include turning off algorithm access permissions, scrambling algorithm and so on (Karizat et al., 2021). Users adopt resistance manipulation strategies.

Research Setting

METHODOLOGY

This study aims to explore the occurrence paths of algorithm manipulation behavior among social media users. In social media, the algorithm recommendation technology of content-sharing social media is the most mature and significant. In recent years, content-sharing platforms such as Redbook, Tiktok, Bilibili, and Douban have nearly 500 million active users in China. These active user groups are familiar with the perception and manipulation of algorithms. Therefore, this study selects content-sharing social media as the research background, and the active users of these media as the research subjects are appropriate.

Instrument Development

Our research primarily targets the user group of content-sharing social media for a questionnaire survey. The questionnaire consists of two parts: demographic information and factors influencing algorithm manipulation behavior. The demographic measurements include the user's gender, education level, major, and the most frequently used content-sharing social media platform. The factors influencing algorithm manipulation behavior examine three dimensions and two types of algorithm

manipulation behavior: user personality traits, information quality, and algorithm quality. These include the user's openness, perceived information narrowness, information redundancy, algorithm fairness, algorithm accountability, algorithm transparency, cooperative algorithm manipulation, and resistant algorithm manipulation. The variables in the questionnaire are measured using multiple indicators. Each indicator uses a five-point Likert scale to measure the second part, with 1-5 representing "strongly disagree," "disagree," "neutral," "agree," and "strongly agree," respectively. The measurement items for each variable are adapted from established measurement items.

Data Collection

To expand the data sources, the formal survey was conducted online through the Wenjuanxing questionnaire system. Over the course of two days, from March 31, 2024, to April 1, 2024, a total of 297 questionnaires were collected. After removing invalid questionnaires with excessively short response times, contradictory answers, or obviously patterned responses, 221 valid questionnaires were obtained, resulting in an effective response rate of 74.41%. Among the valid respondents, there were 77 males, accounting for 34.84%, and 144 females, accounting for 65.16%. In terms of educational level (current students), undergraduates were the main subjects of this survey, with 1.81% being junior college students, 87.33% undergraduates, 9.5% master's students, and 1.34% doctoral and above. Other demographic information is shown in Table 2.

Variables	Categories	Frequency	Percentage (%)
Gender	Male	77	34.84
	Female	144	65.16
	College	4	1.81
Education	Undergraduate	193	87.33
	Postgraduate	21	9.5
	Doctor or higher	3	1.34
	Economics	20	9.05
	Law	10	4.52
Maian	Literature	25	11.31
Major	Science	23	10.41
	Engineering	61	27.6
	Management	43	19.46
	Others	43	19.46
	Redbook	59	26.7
	Tiktok	82	37.1
Social media in most common use	Bilibili	57	25.79
	Douban	3	1.36
	Sina Weibo	6	2.71
	Others	14	6.33

DATA ANALYSIS RESULTS

In the data analysis section of this paper, we first test the reliability and validity of the measurement model. Subsequently, we apply fuzzy-set qualitative comparative analysis (fsQCA) to analyze the configurational paths of users' algorithm manipulation behavior. The Qualitative Comparative Analysis (QCA) method uses set theory to understand the complex combinations of causes and their effects on social phenomena (Kraus et al., 2018). It addresses the shortcomings of both quantitative and qualitative analyses, making it more effective in solving complex causal problems in management practice. The fuzzy-set Qualitative Comparative Analysis (fsQCA), a variant of the QCA method, further enhances calibration and is more suitable for handling continuous data. By assigning membership scores between 0 and 1, it addresses issues of partial membership. This study employs the fsQCA method to explore the combinatorial impact mechanisms of algorithm manipulation behavior among social media users.

Reliability and Validity Testing

In general, the examination of a scale includes reliability and validity testing. This study employed Smart PLS 3 and SPSS 27.0 for reliability and validity testing, with detailed results presented in Tables 3, 4, 5, and 6. Reliability testing reflects the reliability and consistency of the scale content. In the field of social sciences, Composite Reliability (CR) and Average Variance Extracted (AVE) are important indicators of the reliability and consistency of scale content. As shown in Table 3, the CR and AVE values of each latent variable exceed 0.7 and 0.5, respectively. This indicates that the scale designed in this study has good reliability and consistency, meeting the requirements of reliability testing.

Table 3: Analysis of construct reliability.						
	Composite Reliability	Average Variance Extracted (AVE)				
ACM	0.799	0.666				

ARM	0.842	0.73
IN	0.861	0.675
IR	0.855	0.665
0	0.891	0.576
PA	0.797	0.569
PF	0.83	0.62
РТ	0.866	0.683
Note: ACM = Cooperative	Algorithm Manipulation: ARM = Resistant	Algorithm Manipulation: IN = Information Narrowing:

Note: ACM = Cooperative Algorithm Manipulation; ARM = Resistant Algorithm Manipulation; IN = Information Narrowing; IR = Information Redundancy; O = Openness; PF = Perceived Fairness; PA = Perceived Accountability; PT = Perceived Transparency

In the process of scale validity analysis, since the scale and its items in this study are adapted or derived from mature scale systems both domestically and internationally, the content validity of the scale can be guaranteed. Therefore, it is necessary to examine the structural validity of the scale, including convergent validity and discriminant validity. In the humanities and social sciences fields, factor loading is the observation indicator of scale convergent validity, while the square root of AVE and Heterotrait-Monotrait Ratio (HTMT) are observation indicators of scale discriminant validity. Table 4 shows that the factor loadings of all measurement items are greater than 0.7, indicating good convergent validity of the scale.

		Ta	able 4: Factor lo	adings and c	ross-loadings.			
	ACM	ARM	IN	IR	0	PA	PF	PT
ACM1	0.813	0.065	0.015	0.082	0.22	0.131	0.233	0.075
ACM2	0.818	0.112	0.077	0.159	0.193	0.175	0.125	0.206
ARM1	0.055	0.95	0.193	0.221	0.219	0.104	0.092	0.221
ARM2	0.035	0.746	0.185	0.128	0.032	0.075	0.059	0.012
IN1	0.059	0.138	0.777	0.409	0.054	0.111	0.019	0.233
IN2	0.066	0.216	0.894	0.411	0.061	0.16	0.057	0.159
IN3	0.019	0.164	0.789	0.306	0.128	0.168	0.029	0.151
IR1	0.108	0.095	0.302	0.796	0.061	0.049	0.091	0.201
IR2	0.178	0.219	0.367	0.922	0.191	0.061	0.082	0.193
IR3	0.032	0.192	0.47	0.716	0.018	0.039	0.034	0.079
O3	0.244	0.139	0.123	0.065	0.705	0.018	0.059	0.157
O4	0.142	0.154	0.042	0.044	0.792	0.151	0.06	0.078
O5	0.134	0.153	0.114	0.013	0.809	0.148	0.061	0.016
O6	0.134	0.17	0.101	0.101	0.793	0.216	0.057	0.127
07	0.271	0.152	0.037	0.163	0.748	0.161	0.013	0.144
08	0.187	0.057	0.024	0.201	0.701	0.207	0.128	0.104
PA1	0.166	0.107	0.059	0.037	0.184	0.738	0.371	0.206
PA2	0.102	0.081	0.165	0.004	0.069	0.816	0.396	0.27
PA3	0.16	0.055	0.186	0.18	0.209	0.704	0.127	0.416
PF1	0.135	0.029	0.007	0.091	0.007	0.293	0.723	0.112
PF2	0.229	0.084	0.106	0.186	0.11	0.262	0.762	0.11
PF3	0.149	0.095	-0.02	0.073	0.077	0.375	0.87	0.189
PT1	0.171	0.08	0.224	0.256	0.101	0.341	0.099	0.863
PT2	0.081	0.171	0.231	0.222	0.058	0.352	0.158	0.85
PT3	0.173	0.159	0.064	0.018	0.189	0.288	0.18	0.762

Note: ACM = Cooperative Algorithm Manipulation; ARM = Resistant Algorithm Manipulation; IN = Information Narrowing; IR = Information Redundancy; O = Openness; PF = Perceived Fairness; PA = Perceived Accountability; PT = Perceived Transparency

Table 5: Correlations and discriminant validity.								
	ACM	ARM	IN	IR	0	PA	PF	PT
ACM	0.816							
ARM	0.03	0.854						

·								
IN	0.057	0.215	0.822					
IR	0.148	0.216	0.448	0.816				
0	0.253	0.18	0.073	0.138	0.759			
PA	0.188	0.107	0.184	0.063	0.203	0.754		
PF	0.219	0.092	0.035	0.086	0.083	0.395	0.788	
PT	0.172	0.166	0.209	0.199	0.142	0.396	0.177	0.826
Note: ACM	- Cooperative	Algorithm Ma	ninulation · AR	2M = Resistant	Algorithm M	aninulation · IN	I – Informatio	n Narrowing

Note: ACM = Cooperative Algorithm Manipulation; ARM = Resistant Algorithm Manipulation; IN = Information Narrowing; IR = Information Redundancy; O = Openness; PF = Perceived Fairness; PA = Perceived Accountability; PT = Perceived Transparency; The values on the diagonal are the square roots of the AVE values for each variable.

Regarding the evaluation of scale discriminant validity, this study employed three methods. First, as shown in Table 5, the square roots of AVE for each factor are significantly higher than their correlation coefficients with other factors. Second, Table 4 displays that the factor loadings of each measurement item on its corresponding construct are greater than its cross-loadings. Finally, Table 6 demonstrates that the HTMT values for each construct are all below 0.85, indicating significant discriminant validity among constructs. In conclusion, the experimental results indicate that the scale has good convergent and discriminant validity.

	Table 6: HTMT analysis.							
	ACM	ARM	IN	IR	0	PA	PF	РТ
ACM								
ARM	0.188							
IN	0.138	0.291						
IR	0.208	0.27	0.614					
0	0.375	0.198	0.157	0.15				
PA	0.341	0.162	0.285	0.147	0.281			
PF	0.371	0.122	0.112	0.193	0.129	0.604		
PT	0.292	0.203	0.289	0.267	0.198	0.575	0.238	

Note: ACM = Cooperative Algorithm Manipulation; ARM = Resistant Algorithm Manipulation; IN = Information Narrowing; IR = Information Redundancy; O = Openness; PF = Perceived Fairness; PA = Perceived Accountability; PT = Perceived Transparency

Data Calibration

Data calibration is the process of transforming variables into sets and assigning sample membership degrees. It is a crucial step in the fsQCA method. Based on the theoretical model, this study considers openness, information narrowness, information redundancy, perceived fairness, perceived accountability, and perceived transparency as antecedent variables, and cooperative algorithm manipulation and resistant algorithm manipulation as outcome variables. The study uses the direct calibration method, setting values at 0.95 (fully belongs), 0.50 (cross point), and 0.05 (fully does not belong) as anchors, to convert the original values of each variable into fuzzy set membership values within the range of 0 to 1 (Kraus et al., 2018). Factor scores based on PLS are used to combined the items of the constructs.

Necessary Condition Analysis

Before conducting the configurational analysis, this study performed a necessity test on the conditional variables affecting user algorithm manipulation behavior. In qualitative comparative analysis, consistency and coverage are two important indicators. Research indicates that when the consistency of a conditional variable is greater than 0.9, it can be considered a necessary condition for the outcome variable to occur. Coverage is used to describe the explanatory power of the conditions (combinations) X on the outcome Y; a higher number indicates stronger explanatory power (Kraus et al., 2018). This study used fsQCA 4.0 software to perform a necessity test on the factors influencing user algorithm manipulation behavior, with the results shown in Table 7. When the outcome variables were set as cooperative algorithm manipulation, non-cooperative algorithm manipulation, resistant algorithm manipulation, and non-resistant algorithm manipulation, the consistency of all six conditional variables was below 0.9. This indicates that none of the conditional variables is a necessary condition for the outcome variables, suggesting that a single conditional variable will not necessarily lead to the formation of social media user algorithm manipulation behavior. Therefore, it can be seen that the emergence of user algorithm manipulation behavior is not determined by a specific factor but rather by the joint promotion of multiple conditional variables. This study further analyzes the conditional combination paths of user cooperative and resistant algorithm manipulation behavior is not determined by a specific factor but rather by the joint promotion of multiple conditional variables. This study further analyzes the conditional combination paths of user cooperative and resistant algorithm manipulation behavior from a configurational perspective.

Variables	AC	М	~ACM		ARM		~ARM	
	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage
0	0.63	0.67	0.52	0.49	0.62	0.62	0.52	0.52
~0	0.52	0.55	0.65	0.61	0.52	0.51	0.63	0.63
IN	0.62	0.62	0.59	0.53	0.65	0.61	0.55	0.52
~IN	0.53	0.59	0.58	0.58	0.49	0.52	0.59	0.59
IR	0.66	0.66	0.59	0.53	0.66	0.62	0.58	0.55
~IR	0.53	0.60	0.62	0.62	0.53	0.55	0.60	0.64
PF	0.65	0.67	0.54	0.49	0.59	0.56	0.59	0.58
~PF	0.50	0.55	0.64	0.62	0.56	0.58	0.55	0.58
РА	0.67	0.68	0.52	0.47	0.63	0.60	0.57	0.55
~PA	0.48	0.53	0.65	0.64	0.53	0.55	0.58	0.61
РТ	0.67	0.68	0.56	0.51	0.64	0.61	0.57	0.55
~PT	0.52	0.57	0.65	0.64	0.53	0.55	0.60	0.63

Note: ACM = Cooperative Algorithm Manipulation; ARM = Resistant Algorithm Manipulation; IN = Information Narrowing; IR = Information Redundancy; O = Openness; PF = Perceived Fairness; PA = Perceived Accountability; PT = Perceived Transparency

Configurational Analysis

We used fsQCA 4.0 software to construct a truth table and analyze the conditional configurational paths of social media user algorithm manipulation behavior. The study set the frequency threshold at 3 (Schneider & Wagemann, 2012), the raw consistency threshold at 0.8 (Fiss, 2011), and the PRI at 0.65 (Greckhamer et al., 2018). Through fsQCA 4.0 software, three types of solutions can be obtained: complex solutions, parsimonious solutions, and intermediate solutions. Among these, intermediate solutions have moderate complexity and high interpretability (Pappas et al., 2016). Therefore, the intermediate solution was used for the analysis results. The combined analysis of intermediate and parsimonious solutions can be used to distinguish core conditions from peripheral conditions: conditions that exist in both parsimonious and intermediate solutions are considered core conditions, while those that only exist in the intermediate solution are considered peripheral conditions. The results of the configurational path analysis are as follows.

Table 8: Configurational paths of high cooperative algorithm manipulation.

		1
Conditional Variables	Configurational Paths of High Co	operative Algorithm Manipulation
Openness	\bullet	•
Information Narrowing	\otimes	
Information Redundancy		•
Perceived Fairness	•	•
Perceived Accountability	•	•
Perceived Transparency	•	•
Consistency	0.853	0.829
Raw Coverage	0.210	0.249
Unique Coverage	0.051	0.089
Overall Solution Consistency	0.8	322

Overall Solution Coverage	0.300
Note: •indicates the core condition is present;	\otimes indicates the core condition is absent; \bullet indicates the edge condition is
present; Sindicates the edge condition is absent	; blank indicates the condition is irrelevant.

Table 9: Confi	gurational paths o	f low cooperative	e algorithm mani	pulation.	
Conditional Variables	Configura	ational Paths of L	low Cooperative	Algorithm Man	ipulation
Openness	•	\otimes	\otimes	\otimes	\otimes
Information Narrowing	•	\otimes	•	\otimes	\otimes
Information Redundancy	•	•	\otimes	•	\otimes
Perceived Fairness	\otimes	•	\otimes	\otimes	\otimes
Perceived Accountability	\otimes	\otimes	\otimes	\otimes	\otimes
Perceived Transparency	\otimes	\otimes	•	•	\otimes
Consistency	0.834	0.864	0.847	0.859	0.894
Raw Coverage	0.158	0.144	0.150	0.136	0.224
Unique Coverage	0.054	0.030	0.024	0.020	0.084
Overall Solution Consistency			0.830		
Overall Solution Coverage			0.384		

Note: •indicates the core condition is present; \otimes indicates the core condition is absent; •indicates the edge condition is present; \otimes indicates the edge condition is absent; blank indicates the condition is irrelevant.

Table 10: Configurational	paths of high	resistant algorithm	manipulation.

Conditional Variables	Configurational Paths of High Resistant Algorithm Manipulation		
Openness	•		
Information Narrowing			
Information Redundancy	•		
Perceived Fairness	•		
Perceived Accountability	•		

Perceived Transparency	•
Consistency	0.808
Raw Coverage	0.258
Unique Coverage	0.258
Note: \bullet indicates the core condition is present; \otimes present; \otimes indicates the edge condition is absent;	indicates the core condition is absent; • indicates the edge condition is blank indicates the condition is irrelevant.

From the results of Table 8, it can be seen that the overall consistency level of the two configurational paths of high cooperative algorithm manipulation is 0.822, which exceeds the threshold of 0.8, indicating that the configuration results are significant. At the same time, the overall coverage rate of the overall solution reaches 0.300, indicating that these two paths can cover nearly 30% of the cases. Through the analysis of the results, the configurational paths of high cooperative algorithm manipulation of social media users can be summarized as algorithmic system reliability, with the core causal conditions being openness, perceived fairness, perceived accountability, and perceived transparency. Hypothesis H1a is established.

Path 1 (Openness*~Information Narrowing*Perceived Fairness*Perceived Accountability*Perceived Transparency): This path indicates that when social media algorithmic systems provide users with sufficient perceived fairness, accountability, and transparency, and faced with diverse information, users with high openness will choose to cooperate with the algorithm. That is, when the algorithmic system is reliable and the information quality is high, users with high openness will actively use algorithm rules to click on interesting content or actively participate in comments, collection, and other behavior, making the algorithm more accurate in collecting individual preferences to obtain more interesting information.

Path 2 (Openness*Information Redundancy*Perceived Fairness*Perceived Accountability*Perceived Transparency): This path indicates that even if the information users obtain on social media has a certain degree of redundancy, the time cost and cognitive load increase during the process of receiving information. In the case of non-discrimination by the recommendation algorithm, high accountability of relevant platforms, and high transparency of system operation rules, users with high openness will actively explore cooperation with the algorithm, such as clicking "Not Interested," "Too Much Similar Content," etc., in order to obtain higher-quality information to improve their usage experience.

As shown in Table 9, it can be seen that the overall consistency level of the five configurational paths of low cooperative algorithm manipulation is 0.830, which exceeds 0.8, indicating that the configuration results are significant. The overall coverage rate of the overall solution is 0.384, indicating that these five paths can cover nearly 40% of the cases. The configurational paths of low cooperative algorithm manipulation of social media users can be summarized as manipulation ineffective type and manipulation unnecessary type.

As to the ineffective manipulation type, openness, information redundancy, ~perceived fairness, and ~perceived transparency are the core causal conditions. Hypothesis 1b is established. Path 1 shows that even if users have high openness and strong subjectivity, when facing a series of problems existing on social media platforms, such as information silos, algorithm biases, and lack of transparency, their willingness to cooperate with the algorithm is low. Although users subjectively have the consciousness of actively using algorithm rules and trying to change the output results, the trust loss caused by algorithm biases and the lack of sufficient algorithm transparency make it difficult for users to understand and influence the algorithm's decision-making process effectively. Objectively, cooperative manipulation cannot solve the fundamental problem, resulting in ineffective manipulation due to the lack of cooperation level.

As to the unnecessary manipulation type, ~openness and ~perceived accountability are the core causal conditions. Hypothesis 1c is established. On the one hand, users have low openness, weak consciousness of actively cooperating with the algorithm, and show low openness when cooperating with the algorithm, lacking the consciousness of actively cooperating with the algorithm. Low-openness individuals tend to passively accept the results of the algorithm rather than actively participate in the operation and optimization of the algorithm. Due to the lack of motivation and willingness to actively participate, the cooperation level between users and the algorithm is low. On the other hand, the accountability of the algorithmic system is low, and the responsible person for the algorithm platform fails to audit and supervise effectively the adverse effects generated by the recommendation system, etc., leading to a low level of trust in social media platforms, which further affects the trust level of users in cooperative manipulation with the algorithm. Therefore, users consider cooperative manipulation unnecessary.

From the results of Table 10, it can be seen that there is only one configurational path for highly resistant algorithm manipulation, with a consistency level of 0.808, and a total solution coverage rate of 0.258, indicating that this path's configurational results are significant and can cover nearly 30% of the cases. Through the analysis of the results, the configurational paths of high

resistant algorithm manipulation of social media users can be summarized as information cocoon type, with openness, information redundancy, perceived fairness, perceived accountability, and perceived transparency as core causal conditions. Hypothesis H2a is partially established.

In the formed path of high resistant manipulation (Openness*Information Redundancy*Perceived Fairness*Perceived Accountability*Perceived Transparency), the results show that when social media users have a certain degree of openness, in a reliable algorithmic system, the homogenization of information will trigger negative emotions towards information content and social media. It will cause users to resent algorithmic recommendations and adopt resistant manipulation strategies, such as actively exploring methods to block algorithms, deliberately disrupting personal data obtained by algorithms, such as closing permissions, deliberately staying, and other various resistant strategies. Additionally, low-level resistant algorithm manipulation has no solution. So, hypothesis H2b and hypothesis H2c are not established. In the results discussion section, we will further summarize the results and clarify possible explanations for the hypotheses that are not established.

As shown in Table 11, the truth table of the algorithm manipulation occurrence paths is presented. Figure 2 shows that the quadrant diagram of user algorithm manipulation behavior plotted based on the truth table. Due to the configuration paths involving the merging and simplification of cases, i.e., one configuration path can represent multiple different cases, the truth table and the configuration paths do not correspond one-to-one (Schneider & Wagemann, 2012).

Table11: Truth table of the algorithm manipulation occurrence paths.									
Openness	Information	Information	Perceived	Perceived	Perceived	Configuration			
	Narrowing	Redundancy	Fairness	Accountability	Transparency				
1	0	1	1	1	1	ACM1/ARM2			
1	0	0	1	1	1	ACM2			
1	1	1	1	1	1	ACM3/ARM1			
1	1	1	0	0	0	~ACM1			
0	0	1	1	0	0	~ACM2			
0	1	0	0	0	1	~ACM3			
0	0	1	0	0	1	~ACM4			
0	0	0	0	0	0	~ACM5			

Note: ACM=High Algorithm Cooperative Manipulation; ARM=High Algorithm Resistant Manipulation; ~ACM=Low Algorithm Cooperative Manipulation; 0 represents the presence of a conditional variable and 1 represents the absence of a conditional variable.

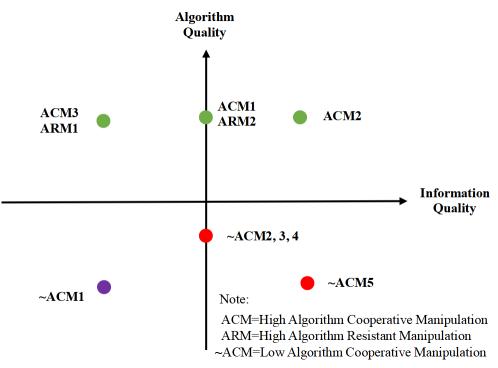


Figure 2: Configuration path quadrants for user algorithm manipulation.

Among them, ACM2 corresponds to path one of high cooperative manipulation, ACM1 and ACM3 correspond to path two of high cooperative manipulation. The occurrence conditions of high cooperative manipulation require the algorithmic system of

social media platforms to be fair, accountable, and transparent, indicating that a reliable algorithmic system is an important factor for users to engage in high cooperative manipulation. In this context, users' cooperative manipulation is effective, and users with openness attempt to change their output results and obtain self-interest information by cooperating with the algorithm, which is feasible: on the one hand, when the information quality is high, users can interact with the algorithm to input data based on their interests to make the algorithm's personalized recommendations more accurate; on the other hand, when users are in a redundant information cocoon or filter bubble for a long time, they will deliberately use algorithm rules to actively give feedback to the algorithm, such as too much similar content. In the low cooperative manipulation path of users, ~ACM1 corresponds to path one of low cooperative manipulation, that is, when open individuals encounter problems such as the opacity of the algorithmic operation mechanism and algorithmic bias, they find it difficult to effectively solve them and thus produce ineffective manipulation of low cooperation; ~ACM2, ~ACM3, ~ACM4, ~ACM5 respectively correspond to paths two to five of low cooperative manipulation, that is, individuals who are not open or relatively closed are difficult to realize the initiative to use algorithm rules to obtain better information services, coupled with the imperfect accountability mechanism of social media, thus engaging in unnecessary low cooperative manipulation. ARM1 and ARM2 correspond to the high resistant configurational path, where users adopt highly resistant algorithm manipulation occurs when the information quality is poor and the algorithmic system is good. When users perceive that the information content is repetitive, they will adopt various resistance strategies to counteract the singularity of information content, such as deliberately staying, searching, and other behavior to disrupt the algorithmic system.

In summary, when social media information and algorithms provide users with a good user experience and sense of security, users engage in cooperative algorithm manipulation behavior. Furthermore, when users perceive that the algorithmic system of social media is reliable and the information obtained is homogeneous, they will adopt a mixed manipulation behavior to change the status quo, that is, high levels of cooperative and resistant algorithm manipulation behavior occur simultaneously.

Robustness Testing

Due to the subjectivity of the assignment in the fuzzy set qualitative comparative analysis (fsQCA) method, it is necessary to conduct robustness testing on the results. Drawing on existing research, this study adopts a specific robustness testing method in set theory, which involves changing the data anchors and altering the analysis threshold, while keeping other steps unchanged (Pappas et al., 2016). The data is reanalyzed using the fsQCA 4.0 software. It is found that the types of configurational paths have not undergone substantial changes. This indicates that the conditional variables for the algorithm manipulation behavior of social media users in this study exhibit good robustness, which can better explain the formation paths of user algorithm manipulation behavior.

DISCUSSION

Theoretical Implications

This study examines the formation mechanisms of social media users' algorithm manipulation behavior from three dimensions: individual, information, and algorithm. It explores the impact of users' openness as a personal trait, information quality, and algorithmic technical characteristics on users' adoption of cooperative and resistant algorithm manipulation. This provides several theoretical insights for current related research.

Firstly, previous research has failed to comprehensively consider both cooperative and resistant algorithm manipulation behavior of users, often focusing on one aspect and predominantly on algorithm resistance. This study categorizes user algorithm manipulation into cooperation and resistance based on the interactive relationship between users and algorithms, broadening the scope of research. By distinguishing between cooperative and resistant algorithm manipulation, the study provides a more nuanced understanding of how users interact with algorithms, shedding light on the diverse strategies users employ to engage with algorithmic systems.

Secondly, in the relevant research on social media users' algorithm manipulation behavior, the research methods are mostly conceptual studies or qualitative research methods such as interviews, lacking quantitative data-driven confirmatory research. Although these studies provide some insights into the topic, the underlying mechanisms of user algorithm manipulation behavior have not been able to form a more complete and closed-loop theory, and the universality of studies based on individual cases remains to be explored. Therefore, it is meaningful for this study to theorize the formation mechanism of user algorithm manipulation behavior using quantitative research methods.

Thirdly, the study explores how the quality of social media information and algorithm affects users' cooperative and resistant algorithm manipulation behavior based on users' subjective initiative, reflected by openness. The study employs a quantitative method through surveys to investigate this research question, providing empirical evidence to fill some gaps in the literature. By examining the impact of information quality and algorithm quality on both cooperative and resistant algorithm manipulation, this research contributes to a deeper understanding of the underlying mechanisms driving users' behavior in algorithmic environments. Additionally, by considering users' subjective initiative as reflected in their openness, the study adds a nuanced perspective to the discussion, highlighting the role of individual characteristics in shaping users' algorithm manipulation behavior.

Finally, we attempt to explore and categorize the configurational paths of social media users' algorithm manipulation behavior. It finds that users' openness significantly impacts their algorithm manipulation behavior. The path for high-level cooperative

manipulation is characterized by a reliable algorithmic system, the path for low-level cooperative manipulation includes unnecessary and ineffective manipulation, and the path for high-level resistant manipulation is characterized by the information cocoon effect. Combining the research hypotheses with the experimental results, it is found that in situations where user openness exists, but algorithm quality and information quality are poor, highly resistant algorithm manipulation behavior does not occur, thereby partially confirming hypothesis H2a. We speculate that when algorithm quality is bad, users' trust in social media is low, so users' willingness to adopt technology is low(Niehaves & Plattfaut, 2014). From the user's perspective, algorithm manipulation is ineffective, leading them to abandon resistant algorithm manipulation strategies. There are no experimental results for lowlevel resistant algorithm manipulation, and hypotheses H2b and H2c are not confirmed. By lowering the frequency threshold and reducing the PRI standard to 0.6, it is found that low-level resistant algorithm manipulation does appear, with a configurational path centered on the absence of openness. This indicates that openness may be one of the important factors influencing low-level resistant algorithm manipulation.

Practical Implications

Based on the previous analysis and summary, and according to the core factors and configurational paths identified in this study that influence user algorithm manipulation behavior, the following recommendations are proposed: Firstly, we should enhance users' subject awareness and cultivate their algorithm literacy. Users' high-level algorithm manipulation behavior is highly correlated with their openness. Enhancing social media users' algorithm literacy can help increase their sense of security and confidence in the digital environment, thereby improving their knowledge and skills related to algorithms. Secondly, we should strengthen information review efforts to avoid homogenized information whirlpools. Social media platforms should provide clear feedback options, such as allowing users to select "too much similar content" or "repetitive content" when interacting with posts. This helps optimize recommendations and prevent user frustration, reducing their algorithm resistance and increasing platform engagement. Lastly, we should establish a clear algorithm accountability system and accelerate the transparency of algorithm design. A clear algorithm accountability system can help reduce issues like algorithmic discrimination and bias against users. Transparency in algorithm design allows users to better understand the algorithms, deepening their knowledge and facilitating more effective interaction and cooperation with the algorithms.

LIMITATIONS AND FUTURE RESEARCH

Given that the study of algorithm manipulation behavior among social media users is a complex and still-exploratory task, this research has the following three limitations: First, due to the limitations of the survey subjects and scenarios, the applicability of this study's conclusions to other contexts and populations requires further verification. Second, in terms of research design, it could further consider using objective behavior data to explore users' algorithm manipulation behavior, thereby broadening the research design longitudinally. Finally, in the study of factors influencing users' algorithm manipulation behavior, there may be other important variables not considered in this research (such as users' algorithm awareness and information literacy, and agreeableness of the Big Five Personality), which can be further explored in future studies.

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