

Algorithmic Resistance among Chinese University Students on Short Video Platforms

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Abstract

The increasing integration of algorithmic recommendation systems in short video platforms has raised concerns about their influence on user autonomy. University students, as active users, may develop varying levels of resistance to algorithmic control, influenced by psychological and social factors. This study aims to examine the relationships between social anxiety, boredom proneness, emotional exhaustion, peer influence, self-control, and algorithmic literacy, and their impact on algorithmic resistance behavior among Chinese university students. The study further investigates the mediating roles of resistance cognition and affective dependence. A structured questionnaire was administered to a sample of Chinese university students using a purposive sampling method. The measurement scales demonstrated acceptable reliability (Cronbach's $\alpha > 0.70$). Structural equation modeling (SEM) was employed to assess direct and indirect relationships among variables, with bootstrapping applied to test mediation effects.

The findings revealed that social anxiety, boredom proneness, emotional exhaustion, and peer influence had varying direct and indirect effects on algorithmic resistance behavior. Resistance cognition and affective dependence played significant mediating roles in several relationships. Fit indices indicated an acceptable model fit (RMSEA = 0.054, CFI = 0.884, TLI = 0.871). The study highlights the complexity of user responses to algorithmic recommendations and underscores the importance of enhancing algorithmic literacy, promoting self-control, and reducing negative

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psychological states to foster healthier digital engagement. The results provide theoretical and practical implications for platform design and digital literacy education.

Keywords: Short Video Platforms, Algorithmic Resistance, Algorithmic Awareness, "Black Box"

Introduction

In the era of mobile internet, smartphones, tablets, and mobile audio-visual devices have become the primary terminals for the public to access virtual networks. Various short video apps have become essential platforms for audiences to obtain information, entertain, and engage in social interactions (Zhou, 2019). Nowadays, various technology companies are incorporating algorithms into their products, resulting in a plethora of digital applications built on algorithmic foundations and mechanisms, such as Douyin, Kwai, and Bilibili.

However, the ethical implications of algorithms have gradually led to societal reflections. Algorithms, as tools used by platforms to enhance user stickiness and commercialization, provide personalized recommendations based on the collection and processing of user data, thereby increasing user engagement and dependency. Due to the "black-box" nature of algorithmic operations, ordinary users find it challenging to have a clear and comprehensive understanding of their functioning, making university students one of the main groups "confronting algorithms."

The current academic focus has been on the way users "outsmart" algorithms, with research revolving around specific resistance tactics, including isolating algorithmic products, reconfiguring algorithmic rules, exerting reverse control over algorithms, and reshaping algorithmic identities. However, there has been limited attention to the "why" aspect, namely, why users resist algorithms, how they resist, and the extent of their resistance. These questions are the primary concerns of this research.

Research's objective

1. To study the main reasons for Chinese college students' resistance to recommendation algorithms in the daily use of short video apps.

2. To analyze the specific resistance behavior of Chinese college students to the algorithm of short video platform and its effect.

3. Investigate the association between algorithmic resistance perception and resistance behavior, focusing on whether there are factors that particularly significantly influence this association.

4. To investigate the role of affective dependence in algorithmic resistance in college students, focusing on whether there are factors that particularly significantly influence this association.

5. To explore ways to crack the "black box" and evade the manipulation of the algorithm platform in view of the algorithm resistance behavior of college students.

Literature review

1. Concept and Research on Algorithms

Zarouali, Brahim, and Vreese (2021) defined algorithmic awareness as individuals' accurate perception of algorithms' behavior in specific media environments and the impact of algorithms on users' consumption and experience of media content. Algorithmic awareness was further categorized into content filtering awareness, automatic decision-making awareness, human-computer interaction awareness, and ethical considerations. Despite the opaque nature of algorithms and the difficulty in tracking or questioning their operations, users can still discover relevant clues through various means. Algorithms particularly reveal themselves during interruptions, unexpected incidents, and breakdowns. Many scholars believe that algorithms have significant negative effects, such as visibility hegemony (Swart, 2021), bias and discrimination (Kulshrestha et al., 2017), information overload (Lin et al., 2020), and privacy breaches (Lam et al., 2006), which may lead to negative psychological and behavioral reactions among platform users.

2. User Autonomy and Research on Algorithmic Resistance

Within the context of algorithms, user autonomy refers to the ability of algorithm users to change the algorithmic system through free choices and independent actions. Giddens (1984:9) pointed out that autonomy not only includes the intentions behind the actor's actions but also encompasses their capacity for action. This ability is closely

related to the emotional practices between users and algorithms. When users possess higher autonomy, they perceive fewer influences of being controlled by algorithms. The concept of "algorithmic resistance" has been introduced to characterize users' interventionist digital agency against recommendation algorithms on social media (Karizat et al., 2021). Compared to other resistance theories, algorithmic resistance focuses on how social media platform users actively resist algorithms using their cognitive and practical abilities when encountering platform algorithms. "When algorithm performance fails to provide a satisfactory user experience, audiences start building their tactical practice space and engage in a series of 'under-the-surface' operations, such as evasion, reconfiguration, embedding, and backlash of algorithmic texts" (Zhang, 2022), thus "escaping" the original logic of algorithms.

Conceptual framework

The conceptual model of algorithmic resistance incorporates six factors and their relationships. It encompasses variables such as boredom proneness, social anxiety, peer influence, self-control, emotional exhaustion, algorithmic literacy. The model explores the interplay among these factors and their impact on university students' intentions and behaviors related to algorithmic resistance. It provides a comprehensive framework for understanding the complexities of algorithmic resistance in the context of short video platforms and offers insights into the underlying mechanisms and dynamics involved

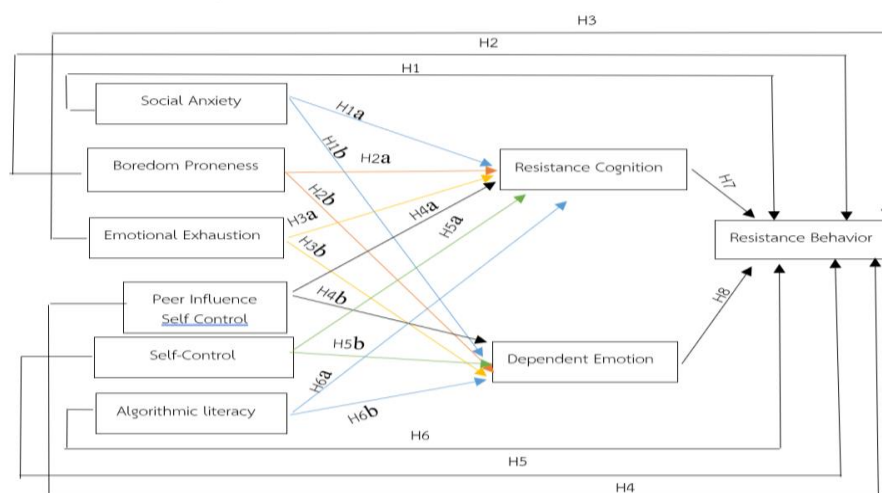


Figure 1 Conceptual Framework for Research on Algorithm Resistance Among College Students

Hypothesis

1. H1: Social anxiety negatively influences college students' algorithm resistance behavior.
2. H1a: College students' social anxiety is negatively correlated with their cognitive resistance to recommendation algorithms in short video apps.
3. H1b: College students' social anxiety is positively correlated with their emotional dependence on recommendation algorithms in short video apps.
4. H2: Boredom proneness negatively influences college students' algorithm resistance behavior.
5. H2a: College students' boredom proneness is negatively correlated with their cognitive resistance to recommendation algorithms in short video apps.
6. H2b: College students' boredom proneness is positively correlated with their emotional dependence on recommendation algorithms in short video apps.
7. H3: Emotional exhaustion negatively influences college students' algorithm resistance behavior.
8. H3a: College students' emotional exhaustion is negatively correlated with their cognitive resistance to recommendation algorithms in short video apps.
9. H3b: College students' emotional exhaustion is positively correlated with their emotional dependence on recommendation algorithms in short video apps.
10. H4: Peer influence positively influences college students' algorithm resistance behavior.
11. H4a: College students' peer influence is positively correlated with their cognitive resistance to recommendation algorithms in short video apps.
12. H4b: College students' peer influence is negatively correlated with their emotional dependence on recommendation algorithms in short video apps.
13. H5: Self-control positively influences college students' algorithm resistance behavior.
14. H5a: College students' self-control is positively correlated with their cognitive resistance to recommendation algorithms in short video apps.
15. H5b: College students' self-control is negatively correlated with their emotional dependence on recommendation algorithms in short video apps.

16. H6: Algorithmic literacy positively influences college students' algorithm resistance behavior.

17. H6a: College students' algorithmic literacy is positively correlated with their cognitive resistance to recommendation algorithms in short video apps.

18. H6b: College students' algorithmic literacy is negatively correlated with their emotional dependence on recommendation algorithms in short video apps.

19. H7: Resistance perception mediates between (a) social anxiety, (b) boredom tendency, (c) emotional exhaustion, (d) peer influence, (e) self-control, and (f) algorithmic literacy and resistance behavior.

20. H8: Dependent emotions mediate between (a) social anxiety, (b) boredom tendency, (c) emotional exhaustion, (d) peer influence, (e) self-control, and (f) algorithmic literacy and resistant behavior.

Methodology

This study adopts a questionnaire survey to investigate algorithmic resistance among Chinese university students who are users of short video apps. Choosing Chinese university students as the research subjects is based on the following considerations: firstly, university students have a certain level of algorithmic awareness and literacy, which serves as the foundation for their algorithmic resistance practices; secondly, university students are among the most frequent users of short video platforms, making them significantly affected by the algorithm mechanisms operating in these platforms; finally, the characteristics of university students' lives provide researchers with convenience in exploring peer influence since they spend considerable time with their peers, making their cognition and behavior more susceptible to peer effects.

The original version of the questionnaire came from two sources: a literature review and in-depth interviews. The interview outline was designed based on a review of existing literature. According to the research results of algorithm resistance of college students at home and abroad, the interview outline is formed. The interview outline is shown in Table 1. According to the interview outline, the study conducted in-depth interviews with 20 interviewees. The formal interview outline has 10 questions. All questions are open-ended, and the order of the questions are fixed. However, the

question can be slightly adjusted based on the respondent's response to get a more accurate answer.

According to accepted research standards (Rovinelli & Hambleton, 1977), items with $\text{IOC} \geq 0.50$ are considered acceptable. In this study, all items met the threshold, with two items ($\text{IOC} = 0.67$) marked for minor revisions to improve clarity before final data collection.

Results

1. Reliability Analysis

Table 1 Reliability Test

Variables	items	Cronbach's α
Social Anxiety	6	0.852
Boredom Proneness	6	0.864
Peer Influence	3	0.872
Self Control	3	0.801
Emotional Exhaustion	4	0.858
Algorithmic Literacy	6	0.822
Algorithm Resistance Cognitive	4	0.858
Algorithm Dependence on Affective	4	0.801
Algorithm Resistance Behavior	10	0.899
Overall	51	0.835

Note. Data and Information from Research

The study conducted reliability analysis using SPSS 24.0 software. The internal consistency coefficients (Cronbach's α) for Social Anxiety, Boredom Proneness, Peer Influence, Self Control, Emotional Exhaustion, Algorithmic Literacy, Algorithm Resistance Perception, Algorithm Dependencies, and Algorithm Resistance Behavior were 0.852, 0.864, 0.872, 0.801, 0.858, 0.822, 0.858, 0.801, and 0.899, respectively. The overall Cronbach's α for all variables was 0.835. Overall, the Cronbach's α coefficients for all nine research variables were above the critical value of 0.7, indicating that the measurement scales used in the study demonstrated good internal consistency. (Refer

to Table 3 for details.)

2. Construct Validity Test

Table 2 Model fitness test

Indicator	Reference Standard	Rating	Actual Measurement Result
χ^2/DF	1~3	Excellent	2.431
	3~5	Good	
RMSEA	<0.05	Excellent	0.054
	<0.08	Good	
GFI	>0.9	Excellent	0.823
	>0.8	Good	
AGFI	>0.9	Excellent	0.799
	>0.8	Good	
PGFI	>0.9	Excellent	0.723
	>0.8	Good	
GFI	>0.9	Excellent	0.884
	>0.8	Good	
TLI	>0.9	Excellent	0.874
	>0.8	Good	
NFI	>0.9	Excellent	0.861
	>0.8	Good	

Source: Data and Information from Research

In this paper, confirmatory factor analysis is used to investigate the structural validity of the model. From Table 4, it can be observed that the absolute fit indices are as follows: the ratio of the chi-square to degrees of freedom (χ^2/DF) is 2.431, which is less than 3, indicating a good fit; the Root Mean Square Error of Approximation (RMSEA) is 0.054, which is less than 0.08, indicating a good fit; the Goodness-of-Fit Index (GFI) is 0.823, which is greater than 0.8, indicating a good fit; the Adjusted Goodness-of-Fit Index (AGFI) is 0.799, which is close to 0.8, indicating a good fit.

As for the parsimony fit indices, the Parsimony Goodness-of-Fit Index (PGFI) is

0.723, which is greater than 0.5, indicating a good fit.

Furthermore, in the incremental fit indices, the GFI is 0.884, the Tucker-Lewis Index (TLI) is 0.874, and the Normed Fit Index (NFI) is 0.861, all of which are greater than 0.8, indicating an ideal fit.

Based on the model complexity and sample size, the fit results are deemed acceptable, indicating that the model exhibits good construct validity.

3. Estimation and correction of model parameters

Table 3 Model fitting indexes and fitting results

Fitting index	Fitting result	The ideal standard value
Absolute fitting index	$\chi^2=2306.605$	—
	$\chi^2/DF = 2.431$	< 3
	P=0.13	≥ 0.05
	RMSEA=0.054	< 0.08
	GFI=0.823	> 0.8
	AGFI=0.799	> 0.8
Streamline fitting index	PGFI=0.723	> 0.5
Value-Added fitting index	CFI=0.884	
	TLI=0.874	> 0.8
	NFI=0.861	

In structural equation analysis, Maximum Likelihood (ML) is used to estimate the model parameters, and several fitting indexes are used to evaluate the fit of the model. These indicators are intended to help this paper understand the degree of fit between the model and the observed data, so as to judge the quality and accuracy of the model.

It can be seen from the above table that in the absolute fit index, the value of χ^2/DF is 2.431, which is less than 3, indicating an ideal fit. The RMSEA is 0.054, less than 0.08, and the fit is ideal. The GFI was 0.823, greater than 0.8, and the adaptation was good. The AGFI is 0.799, close to 0.8, and the fitting result is good. In the thin fit index, PGFI is 0.723, greater than 0.5, indicating ideal fit. In the value-added fit index, GFI is

0.884, TLI is 0.874, NFI is 0.861, all of which are greater than 0.8, and the fit result is ideal. Therefore, based on the model complexity and sample size, the fitting results are acceptable.

4. Direct effects test

Table 6 Analysis of model path coefficients

Hypothesis		Paths	Non-standardize	Standardization	S.E	C.R.	P	Accept or not
H7a	Indirect effects	SA→RC	-0.280	-0.292	0.067	-4.342	0.000	Accept
H7b		BP→RC	-0.255	-0.218	0.063	-3.474	0.000	Accept
H7c		EE→RC	-0.149	-0.131	0.066	-1.974	0.048	Accept
H7d		PI→RC	0.230	0.242	0.060	4.067	0.000	Accept
H7e		SC→RC	0.309	0.309	0.069	4.483	0.000	Accept
H7f		AL→RC	0.171	0.188	0.076	2.488	0.013	Accept
H8a		SA→DA	0.103	0.082	0.061	1.340	0.180	Reject
H8b		BP→DA	0.151	0.17	0.064	2.656	0.008	Accept
H8c		EE→DA	0.355	0.239	0.065	3.694	0.000	Accept
H8d		PI→DA	-0.162	-0.13	0.056	-2.345	0.019	Accept
H8e		SC→DA	0.047	0.036	0.064	0.558	0.577	Reject
H8f		AL→DA	-0.387	-0.324	0.075	-4.342	0.000	Accept
	Mediation	RC→RB	0.634	0.405	0.048	8.427	0.000	Accept
		DA→RB	-0.117	-0.098	0.036	-2.736	0.006	Accept
H1	Direct effects	SA→RB	-0.048	-0.032	0.034	-0.939	0.347	Reject
H2		BP→RB	-0.099	-0.071	0.034	-2.113	0.035	Accept
H3		EE→RB	-0.102	-0.058	0.035	-1.649	0.049	Accept
H4		PI→RB	0.087	0.058	0.031	1.905	0.050	Accept
H5		SC→RB	0.126	0.081	0.036	2.272	0.023	Accept
H6		AL→RB	0.115	0.081	0.041	1.984	0.047	Accept

Note: *p < 0.05, **p < 0.01, ***p < 0.001

The maximum likelihood method is used to substitute the sample data into the above structural equation for analysis. After comparing the original model with a set of modified models, the model with the least modification is selected on the premise that the fitting index meets the requirements. Table 6 lists the parameter estimates. First, self-control has the greatest effect on the algorithm's resistance behavior, with Non-standardized coefficient =0.126, $P=0.023$. The second is the influence of algorithm literacy on algorithm resistance behavior, the non-standardized coefficient =0.115, $P=0.047$. Peer influence also has a positive predictive effect on the algorithm's resistance behavior, and the non-standardized coefficient is =0.087, $P=0.057$. In addition, boredom tendency and emotional exhaustion can negatively predict the resistance behavior of the algorithm, and their non-parametric coefficients are -0.071 and -0.058, respectively, and their P-values are 0.035 and 0.089, respectively. However, social anxiety did not show significant influence on the algorithm's resistance behavior, with non-parametric coefficient =-0.048, $P=0.347$.

5.Path and Mediation Effects Test

Firstly, the path parameters of the model show that algorithm resistance cognition has a positive influence on algorithm resistance behavior ($\beta=0.634$, $p=0.000$), while algorithm dependency affect has a negative influence on algorithm resistance behavior ($\beta=-0.117$, $p=0.006$). In the assessment of mediation effects within the structural equation model, if the bootstrap 95% confidence interval of the mediation effect does not include zero, it indicates that the mediation effect of the mediator variable in that path is significant.

The results of the mediation effects test are shown in Table 4.20. The test results reveal that social anxiety has a significant indirect effect on algorithm resistance behavior through algorithm resistance cognition ($\beta=-0.280$, $p=0.000$), while the indirect effect through algorithm dependency affect is not significant ($\beta=0.103$, $p=0.180$). Therefore, it can be concluded that only algorithm resistance cognition plays an effective mediating role between social anxiety and algorithm resistance behavior.

Considering that the direct influence of social anxiety on algorithm resistance behavior is not significant ($\beta=-0.048$, $p=0.347$), it can be inferred that algorithm resistance cognition acts as a complete mediator. Boredom tendency has a significant indirect

effect on algorithm resistance behavior through algorithm resistance cognition ($\beta=-0.255$, $p=0.000$), and the indirect effect through algorithm dependency affect is also significant ($\beta=0.151$, $p=0.008$). Thus, it can be concluded that both algorithm resistance cognition and algorithm dependency affect play effective mediating roles between boredom tendency and algorithm resistance behavior.

Emotional exhaustion has a significant indirect effect on algorithm resistance behavior through algorithm resistance cognition ($\beta=-0.149$, $p=0.048$), and the indirect effect through algorithm dependency affect is also significant ($\beta=0.355$, $p=0.000$). Therefore, it can be concluded that both algorithm resistance cognition and algorithm dependency affect play effective mediating roles between emotional exhaustion and algorithm resistance behavior.

Peer influence has a significant indirect effect on algorithm resistance behavior through algorithm resistance cognition ($\beta=0.230$, $p=0.000$), and the indirect effect through algorithm dependency affect is also significant ($\beta=-0.162$, $p=0.019$). Thus, it can be concluded that both algorithm resistance cognition and algorithm dependency affect play effective mediating roles between peer influence and algorithm resistance behavior.

Self-control has a significant indirect effect on algorithm resistance behavior through algorithm resistance cognition ($\beta=0.309$, $p=0.000$), while the indirect effect through algorithm dependency affect is not significant ($\beta=0.047$, $p=0.577$). It can be inferred that only algorithm resistance cognition plays an effective mediating role between self-control and algorithm resistance behavior.

Algorithm literacy has a significant indirect effect on algorithm resistance behavior through algorithm resistance cognition ($\beta=0.171$, $p=0.013$), and the indirect effect through algorithm dependency affect is also significant ($\beta=-0.387$, $p=0.000$). Therefore, it can be concluded that both algorithm resistance cognition and algorithm dependency affect play effective mediating roles between algorithm literacy and algorithm resistance behavior.

Table 7 Mediation effect test

Hypothesis	Path	Estimate	SE	Biased-corrected 95%CI			Percentile 95%CI			Accept or not
				lower	upper	P	lower	upper	P	
H1a	SA→RC→RB	-0.118	0.03	-0.19	-0.067	0	-0.187	-0.064	0.001	Accept
H1b	SA→DA→RB	-0.008	0.006	-0.032	0.001	0.156	-0.028	0.003	0.242	Reject
H2a	BP→RC→RB	0.069	0.038	0.021	0.13	0.014	0.02	0.128	0.016	Accept
H2b	BP→DA→RB	0.021	0.01	0.007	0.052	0.007	0.005	0.047	0.013	Accept
H3a	EE→RC→RB	-0.053	0.029	-0.115	-0.004	0.07	-0.111	-0.002	0.084	Accept
H3b	EE→DA→RB	-0.023	0.006	-0.052	-0.007	0.006	-0.048	-0.006	0.011	Accept
H4a	PI→RC→RB	0.098	0.031	0.054	0.157	0.001	0.051	0.152	0.002	Accept
H4b	PI→DA→RB	0.013	0.007	0.002	0.036	0.03	0.001	0.032	0.049	Accept
H5a	SC→RC→RB	0.125	0.04	0.073	0.187	0.001	0.068	0.181	0.002	Accept
H5b	SC→DA→RB	-0.004	0.013	-0.021	0.008	0.456	-0.017	0.01	0.619	Reject
H6a	AL→RC→RB	0.076	0.056	0.02	0.149	0.019	0.019	0.147	0.022	Accept
H6b	AL→DA→RB	0.032	0.041	0.012	0.069	0.005	0.009	0.063	0.011	Accept

Note: *p <0.05, **p<0.01, ***p<0.001

In summary, algorithm resistance cognition serves as a mediator in the relationships between social anxiety, boredom tendency, emotional exhaustion, peer influence, self-control, algorithm literacy, and algorithm resistance behavior. Algorithm dependency affect, on the other hand, only acts as a mediator in the relationships between boredom tendency, emotional exhaustion, peer influence, algorithm literacy, and algorithm resistance behavior as shown in Table 7 below.

Discussion and conclusions

Through interviews with 20 samples and questionnaire data from 486 valid samples, this study verified human resistance to the algorithm by combining qualitative and quantitative methods. The results show that boredom tendency and social anxiety have significant negative effects on algorithmic resistance behavior, while self-control

and algorithmic literacy have significant positive effects on algorithmic resistance behavior. However, peer influence has no expected positive effect on the algorithm resistance behavior, and emotional exhaustion has no expected negative effect on the algorithm resistance behavior, but it increases the algorithm resistance behavior of college students. Specific conclusions are as follows:

First of all, the expected hypothesis of this study is that college students can rationally view the algorithm myth, so if they are influenced by peers, they will improve their algorithm cognition and thus increase their algorithm resistance behavior. In other words, peer influence will positively affect college students' algorithm resistance behavior, but the research conclusion is not consistent with our expected hypothesis. On the contrary, peers negatively affect college students' algorithm resistance behavior. According to the in-depth interview results, college students rarely communicate with each other about algorithm literacy or cognition, and instead recommend each other to browse interesting videos. Or when college students see that their friends are scrolling Tiktok, they will join in, thus increasing the frequency of using social media. This use favors passive dependence rather than active resistance.

Secondly, this study finds that although algorithmic cognition such as algorithmic literacy can positively affect users' algorithmic resistance. The surveyed college students' emotional attitude towards algorithms tends to be neutral and negative on the whole, which means that they are not blindly immersed in the convenience brought by algorithms, but can still clearly recognize the drawbacks of algorithms as intermediaries in Internet platforms. It can also be seen from the results of theme modeling and word frequency analysis that they can realize the priority of the platform's interest pursuit under the algorithm proxy, as well as the invasion of personal privacy caused by it, the homogenization and extreme of guiding views, and the occupation of personal time. At the same time, they are also questioning the objectivity and authenticity of the content under the algorithm recommendation. The problem is that although a large number of college students are aware of the existence of the platform algorithm and have certain resistance intentions or resistance behaviors, their resistance methods are relatively mild.

Finally, in the interactive game with the algorithm, young users are still passive.

Generally speaking, emotional dependence such as boredom tendency, emotional exhaustion and boredom tendency will greatly weaken the resistance to the algorithm, which is also the expected hypothesis of the paper. However, the results show that emotional exhaustion does not negatively affect the algorithm resistance, but increases the algorithm resistance behavior of college students. This may have something to do with college students being less inclined to use social media when they are experiencing emotional exhaustion.

The above research results provide useful insights for this paper to understand the behavioral responses of individual college students in the face of algorithm recommendation.

Recommendation

1.Platform context and algorithm black box cracking

First of all, Enhance platform transparency to help users better understand how algorithms work, reducing distrust and resistance. Short video media and technology companies should adopt the principles of algorithm element transparency, procedure transparency, and background transparency to improve algorithm transparency.

Second, Strengthen user information privacy protection and minimize tracking of sensitive information. Sensitivity data, such as financial data, bank cards, personal biometric data, tracking data, health data, and credit data, should be treated with utmost care to avoid privacy breaches and potential harm. Categorization and classification of personal data are essential in risk identification and have become a consensus in academia.

Finally, Improve and optimize recommendation algorithms to filter out inappropriate content. As user demands shift from entertainment to knowledge acquisition, it is necessary for short video apps to reduce fragmented entertainment content. Encourage content producers to create valuable and high-quality content, construct reasonable value matrices, and align content in a way that provides users with meaningful value through algorithmic recommendations.

2.User subject context and black box cracking

On the one hand, it can be considered to increase the user subjectivity in data

construction, that is, to establish the economic rights and interests of users in the era of big data. Take intelligent recommendation algorithms as an example. At present, the intelligent recommendation of personalized content such as Tikto is mostly pre-selected and personalized, that is, personalized content generated entirely by algorithms, usually without the active selection and participation of users (Nie and Song, 2020).

On the other hand, special attention should be paid to the user subjectivity in the construction of digital ethics. For example, to strengthen the user's algorithm literacy education, the public should learn and understand the necessary algorithm common sense, not to rely too much on the algorithm, but also be aware of the negative externalities of the algorithm, and give careful evaluation and cognition of the systematic impact of the algorithm, not only to fight for the reasonable right to know the algorithm "black box", but also to rationally produce and protect personal information. Prevent the risks and negative consequences that algorithms may bring.

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