The Impact of Recommendation Content Homogenization on Users' Algorithm Resistance Behavior: A Dual-Path Study Based on Emotion and Cognition

Lexuan Xu
College of Information and Electrical Engineering,
China Agricultural University
Beijing 100083, China
lexuanxu2026@126.com

Abstract

Leveraging recommendation algorithms enables applications to deliver content with high precision, but simultaneously fosters content homogenization, which amplifies users' algorithmic resistance behaviors. However, the existing literature has not yet revealed the underlying mechanisms in depth. Drawing on the conservation of resources (COR) theory, this study examines how recommendation content homogenization affects users' algorithmic resistance behavior through specific psychological mechanisms. Findings from 323 Chinese college students reviewed that recommendation content homogenization significantly and positively affects users' algorithm resistance behavior. It was also found that fatigue experience and knowledge anxiety both act as significant mediators, with the mediating effect of knowledge anxiety notably greater than that of fatigue experience. Furthermore, user's algorithm literacy significantly and negatively moderates the impact of recommendation content homogenization on fatigue experience and knowledge anxiety, respectively. By integrating emotional and cognitive perspectives, this study provides new insights into the underlying mechanisms between algorithmic content homogeneity and algorithm resistance behavior. The research findings have unraveled the theoretical "black box" between recommendation content homogenization and algorithm resistance behaviors, thereby holding practical reference value for the development and improvement of mobile recommendation systems.

Keywords: Recommendation Content Homogenization; Fatigue Experience; Knowledge Anxiety; Algorithm Literacy; Algorithm Resistance Behavior

Introduction

The development of mobile internet technology has led to an overwhelming flow of information with diverse access channels, leaving the public feeling overwhelmed by vast amounts of content. An inherent contradiction exists between people's limited capacity to process and utilize information and the limitless availability of data, causing many to

experience information overload. In response, various applications—including short video, social media, e-commerce, and news platforms—are increasingly adopting algorithm-driven interactive content distribution models. These models aim to provide personalized content recommendations to mitigate information overload, enhance user experience, and boost user engagement. For example, Bilibili collects users' usage data (shares, feeds, coins, comments, likes, favorites, plays), uses algorithm technology to analyze the data, and subsequently recommends content aligned with user preferences. Tencent, Ali, and Tiktok and other enterprises take algorithms as the core of their main products and businesses, collect user data as algorithm input, and use the algorithm recommendation results for personalized App push services.

Algorithmic platforms capitalize on human curiosity and convenience by recommending content precisely tailored to users' interests. However, when users are immersed in information flows that align with their personal preferences for a long time, they will face the predicament of increasingly homogeneous information. This not only promotes the forming of the "information cocoon" phenomenon, but also exacerbates users' cognitive biases and rigid thinking[1]. In the process of interacting with recommendation algorithms, users usually base their actions on their own perception and understanding of algorithms, and try to make up for the gaps in their understanding of algorithm systems through imagining the operation mode of algorithms, thereby guiding themselves on how to use algorithms more effectively. Existing studies have found that users engage in algorithmic resistance in order to mitigate potential negative impacts caused by recommendation content homogenization, thereby seeking to optimize the recommendation effect of the platform[2]. Algorithm resistance serves as a crucial coping mechanism through which App users consciously and proactively counteract the negative effects of algorithms. It also represents a key behavioral manifestation that authentically reflects users' evaluations and attitudes toward the quality of algorithm-driven recommendations. Therefore, research on algorithm resistance holds significant implications for enhancing user oversight of algorithms and optimizing platform algorithms [3].However, research on user behavior under recommendation algorithms remains in its early stages. Existing studies still exhibit the following limitations. First, the extant literature employs qualitative grounded theory approaches to explores the influencing factors of algorithm resistance behaviors [4], yielding conclusions confined to practical explanations with limited generalizability. Few scholars have adopted questionnaire-based empirical methods to investigate the underlying mechanisms of why recommendation content homogenization triggers users' resistance behaviors. Second, critical reflections on the negative effects of algorithms predominantly follow an "algorithm-centric" perspective [5], while neglecting the user-subject perspective. Particularly, platform users' psychological perceptions of recommendation algorithms and their agentic interactive practices when encountering algorithms have been overlooked [6]. Consequently, our understanding of the intrinsic mechanisms through which recommendation content homogenization leads to algorithm resistance remains inadequate. Third, existing studies have yet to examine the boundary role of users' algorithm literacy. Since different users possess varying levels of understanding and perceptions of algorithms, their psychological experiences in response to recommendation content homogenization may also differ significantly.

Drawing upon conservation of resources (COR) theory, this study examines the process mechanisms through which recommendation content homogenization leads to users' algorithm resistance behaviors from both emotional and cognitive pathways. From the emotional resources perspective, while algorithmic recommendations are based on users' personal information and preferences, they essentially constitute a form of "algorithmic control" that diminishes users' autonomy in information seeking [7,8]. As noted in prior research, fatigue arises in those situations where someone faces high demand, but does not possess the required ability to achieve the goals set [9,10]. When homogenized algorithmic content fails to meet users' hedonic or utilitarian value expectations, their fatigue experience intensifies. To mitigate this loss of autonomy

and fatigue, users may engage in algorithm resistance behaviors as a coping strategy to alleviate negative experiences caused by resources depletion. From the cognitive resources perspective, while algorithmic recommendations appear to provide "personalized information curation", they actually reduce information diversity, limiting users' exposure to varied perspectives and narrowing their worldview, thereby inducing knowledge anxiety[11]. When content becomes excessively homogenized, the gap between users' acquired knowledge and expected knowledge gradually widens, creating a void in the data-to-knowledge transformation process [12], which further exacerbates users' knowledge anxiety. By integrating these two mediating mechanisms combining both emotional and cognitive pathways, this study extends and enriches research on the antecedents of algorithm resistance behaviors, while contributing to our understanding of why users adopt resistant behaviors in response to recommendation content homogenization.

We also go one step further and examine an important boundary condition on the extent to which recommendation content homogenization is resource depleting and detrimental to users. Given that users are the recipients of algorithmic recommendations, we identify user characteristics that should impact the extent to which recommendation content homogenization is treated. Specifically, we examine users' algorithm conscientiousness [13-15], theorizing that users' algorithm literacy will weaken the detriments of recommendation content homogenization on their fatigue experience and knowledge anxiety.

To address the gaps in existing research, this study, grounded in the conservation of resources (COR) theory, explores the impact of the recommendation content homogenization on users' algorithm resistance behaviors. It clarifies the mediating roles of fatigue experience and knowledge anxiety in the aforementioned relationship and their differential effects, providing a more rational theoretical explanation for the phenomenon of user behavior on algorithmic recommendation platforms. In addition, this study explores the moderating role of algorithm literacy in the relationship between content homogenization in recommendations and users' resistance behaviors. Through examining these relationships, this research is the first to identify fatigue and knowledge anxiety as key mediating mechanisms between algorithmic content homogenization and algorithm resistance behavior, thereby contributing to the study of user behaviors in algorithmic App usage. Research on algorithm resistance based on COR theory helps to demystify the connection between recommendation content homogenization and user resistance. Practically, understanding user algorithm resistance behaviors can assist App developers in identifying the causes behind user resistance and optimizing recommendation algorithms to improve user experience.

THEORY AND HYPOTHESES

Recommendation Content Homogenization and Algorithm Resistance Behavior

With the explosive growth of internet information, recommendation algorithms have played a crucial role in helping users filter content of interest from massive data [16-18]. However, this personalized recommendation approach has also led to negative consequences, notably recommendation content homogenization. Recommendation content homogenization refers to the phenomenon where recommendation systems excessively favor suggesting content highly similar to users' past interactions or expressed preferences, consequently narrowing and homogenizing the scope of information users encounter[19-21] . Similarity in recommended content may manifest in converging themes and singular perspectives [15,22]. Such homogenization may lead to detrimental effects including information cocoons, filter bubbles, and echo chambers, ultimately constricting users' information intake and reducing informational diversity [21,23-26].

Existing research has found that when recommendation systems overemphasize precise matching, users may experience the pressures of "information narrowing" and "information redundancy" [20]. Information narrowing refers to the contraction of content diversity accessible to users, while information redundancy manifests as repeated

exposure to similar or duplicated content. These negative experiences erode users' trust in recommendation systems and elicit aversion toward algorithmic recommendations [20,27]. Concurrently, recommendation content homogenization results in deteriorating information quality. Existing research demonstrates that such quality degradation induces psychological reactance among users, subsequently prompting coping strategies [28]. The deeper conflict lies in the widespread user expectation that algorithms should deliver the value of content diversity, which clashes with the reality of homogenized content. When users desire to update their knowledge and broaden their horizons through algorithmically recommended content, yet simultaneously have to endure its monotonous repetition, they are plunged into a state of cognitive dissonance as proposed by Festinger, triggering psychological tension [29-31]. To alleviate such discomfort, users often instinctively resort to resistance behaviors [29]; in this context, such behaviors manifest as algorithm resistance [20,32]. This behavior primarily manifests at two levels. On one hand, to counter issues like information cocoons, some social media users proactively adopt strategies to "manipulate the algorithm" in order to obtain content more aligned with their needs [19,33,34]. Specifically, users may deliberately search for or click on content diverging from their usual preferences, or attempt to "trick" algorithms by adjusting settings or clearing browsing history, thereby disrupting homogenized information flows [19]. Some may directly report excessive content homogenization to platforms [19]. On the other hand, studies indicate that homogenized information streams create psychological pressure, inducing reactance that motivates avoidance behaviors [20]. For instance, adolescent users of short-video Apps may develop both resistance intentions and actual algorithm resistance behaviors [32]. Such avoidance manifests through reduced platform dependency, seeking alternative information sources, or complete platform abandonment. Therefore, this study proposes the following hypothesis:

H1: Recommendation content homogenization positively affects algorithm resistance behavior.

Recommendation Content Homogenization and Fatigue Experience

The core objective of recommendation algorithms is to enhance user experience and engagement by analyzing vast amounts of data, including browsing history, preferences, and social interactions, to deliver personalized and relevant content recommendations [35,36]. However, this "catering to preferences" personalization mechanism may lead users to be consistently exposed only to information that closely aligns with their existing interests, thereby creating "information cocoons" [21,24]. Research has found that once the algorithm has satisfactorily matched users with content, a substantial amount of similar content will persistently populate the user's recommended information stream over an extended period [37]. This recommendation content homogenization diminishes users' autonomy in information seeking.

Fatigue experience refers to the psychological and emotional exhaustion users develop through prolonged interaction with algorithms [14]. From the perspective of emotional resources, algorithm-driven content recommendations based on users' personal information and preferences lead to recommendation content homogenization, which diminishes users' autonomy in information seeking [7-10]. When algorithmic recommendations reduce users' autonomy and fail to meet their expectations for either hedonic value (e.g., entertainment, relaxation) or utilitarian value (e.g., acquiring practical information, problem-solving), users' sense of fatigue intensifies, resulting in fatigue experience[19]. Research demonstrates that in recommendation systems, repeated exposure to overly similar content or material that only matches short-term interests can quickly lead to disengagement and fatigue experience [38]. In e-commerce platforms, for instance, continuous recommendations of similar products aligned with users' interests may induce weariness [39]. Lin's (2008) study indicates that in social media, a plethora of homogeneous information can decrease user interest[40]. Furthermore, Liu et al. (2020) discovered that a large amount of similar information reduces the entertainment value of App content and induces user fatigue [37]. Based on

this, the following hypothesis is proposed:

H2: Recommendation content homogenization positively influences users' fatigue experience.

The mediating role of fatigue experience

Fatigue experience refers to the psychological and emotional exhaustion that users develop through prolonged interaction with algorithms, manifesting as weariness, frustration, and diminished interest [14,41]. Existing common recommendation algorithms have a strong accuracy but a weak diversity. When algorithm recommendation content homogenization fails to satisfy users' hedonic or utilitarian values, it triggers fatigue experience. Existing studies have demonstrated that long-term exposure to the same information can lead to users' fatigue experience [38,42], and may trigger further coping behaviors [20,32,43].

The conservation of resources (COR) theory, an offshoot of stress research, posits that individuals are constantly and actively striving to maintain, protect, and build resources they perceive as valuable, while responding to threats of actual or potential resource loss [43]. Conservation of resources (COR) theory posits that resources may encompass material (e.g., money, possessions), conditional (e.g., employment, family), personal characteristic (e.g., skills, health), and energetic (e.g., time, energy) dimensions [44]. In accordance with the primacy of resource conservation, when confronted with the loss of resources, individuals are inclined to take preemptive action to prevent further loss of resources and avoid spiraling into the loss spiral, thereby minimizing the extent of the depletion[45,46].

Recommendation content homogenization may lead to users' fatigue experience, during which their resources such as energy, concentration, and emotional capacity are being depleted. First, users spend time browsing large amounts of repetitive or irrelevant information without finding genuinely interesting or valuable content, resulting in wasted time and energy [38,47]. Second, due to the echo chamber effect, the information users encounter becomes increasingly narrow, potentially causing them to miss important or diverse information, thereby impairing their utilitarian resources for knowledge acquisition and perspective broadening [48]. Finally, persistent feelings of boredom, disappointment, and dissatisfaction deplete users' psychological resilience, sense of enjoyment, and exploratory motivation, leading to mental fatigue [49,50]. To cope with these resource losses, users may engage in algorithm resistance behaviors [20,32,43,51].Based on the above discussion, the following hypothesis is proposed:

H3: Recommendation content homogenization leads to user's algorithm resistance behavior by triggering user's fatigue experiences, that is, user's fatigue experience plays a mediating role between recommendation content homogenization and user's algorithm resistance behavior.

Recommendation content homogenization and knowledge anxiety

Anxiety arises when individuals experience tension and distress in uncertain environments, and their autonomic nervous system triggers a series of coping behaviors to deal with potential threats. User anxiety in social media is mainly manifested as physiological and psychological tension and a sense of oppression when using social media platforms [52]. The development of the internet has led to a dramatic increase in knowledge and information, making anxiety about knowledge and information increasingly prominent. Research categorizes knowledge anxiety into two primary types: (1) anxiety stemming from outdated knowledge or knowledge deficiency, and (2) anxiety related to knowledge discrimination, quality concerns, and information overload[53,54]. The first category of knowledge anxiety stems from the rapid pace of knowledge renewal, where users perceive a lack of knowledge or difficulty in accessing certain types of knowledge, leading to worries about becoming outdated: when people's desire for knowledge increases but the media and other information channels around them are unable to provide what they need, anxiety is induced.

From the perspective of cognitive resources, algorithmic content recommendation, while ostensibly offering "personalized information," actually diminishes informational diversity. This restricts users' exposure to varied content and narrows their perspectives, trapping them in a homogeneous information environment. Such conditions may induce a sense of being unable to access certain knowledge, thereby triggering knowledge anxiety

rooted in perceived knowledge deficiencies [11]. When recommendation content homogenization becomes severe, the gap between users' required knowledge and expected knowledge gradually widens, creating a void in the data-to-knowledge conversion process [12]. This makes users acutely aware of their knowledge gaps, fostering anxiety about intellectual obsolescence and intensifying their knowledge anxiety. Therefore, the following hypothesis is proposed:

H4: Recommendation content homogenization positively affects user knowledge anxiety.

The mediating role of knowledge anxiety

The original intention of personalized recommendation systems was to help users cope with information overload [55] by reducing the cognitive resources (e.g., attention, decision-making time, and processing load) invested in information filtering. Through precise recommendations, users can locate desired information more efficiently, thereby improving information acquisition effectiveness [56]. However, the use of recommendation systems may lead to recommendation content homogenization, giving rise to "information cocoons," "filter bubbles," and "echo chambers," which constrain users' information exposure and diminish content diversity [21,23-26]. Under such circumstances, users are repeatedly exposed to content with similar themes, viewpoints, or styles [57 58]. This monotonous and repetitive information flow fails to utilize users' cognitive resources effectively; instead, it may result in cognitive resource wastage, as the returns (diverse new knowledge or perspectives) from the cognitive effort invested remain limited.

When people's thirst for knowledge increases, but the media or other means around them cannot meet their needs, it triggers knowledge anxiety[53]. Repeated exposure to such homogenized content may lead users to worry about the one-sidedness of their information intake, fear missing critical information, or recognize gaps in their knowledge during social interactions, thereby inducing knowledge anxiety [23]. This anxiety stems from the perceived "loss" of a core cognitive resource—knowledge diversity and breadth. According to COR theory, when confronted with the loss of resources, individuals are inclined to take preemptive action to prevent further loss of resources and avoid spiraling into the loss spiral, thereby minimizing the extent of the depletion.[45,46] To counter this threat of resource depletion, users adopt various strategies to safeguard or replenish their resources. Algorithm resistance serves as one such proactive coping mechanism [20,32,43]. Based on the above discussion, the following hypothesis is proposed:

H5: Recommendation content homogenization leads to user knowledge anxiety, which ultimately leads to user's algorithm resistance behavior. That is, user knowledge anxiety mediates the relationship between the recommendation content homogenization and user algorithm resistance behavior.

The moderating effect of algorithmic literacy

Algorithm literacy refers to the comprehensive manifestation of users' ability to understand, evaluate, and effectively utilize algorithmic systems [59-61]. It encompasses awareness of how algorithms work, the ability to identify algorithmic biases, and the skills to intervene in their operations when interacting with recommendation systems [15,59,62]. Algorithm literacy can mitigate the fatigue experience and knowledge anxiety caused by recommendation content homogenization through its functions in the following three aspects.

First, algorithm literacy empowers users with a sense of control over information seeking, reducing fatigue caused by passive acceptance. Research indicates that users with high algorithm literacy possess a clearer understanding of how algorithms operate[14,62]. They are able to discern the patterns, mechanisms, and potential limitations of algorithmic recommendations[15]. When users comprehend these mechanisms, they are empowered to take proactive actions to manage their online experiences, rather than passively accepting algorithmic arrangements [15]. For example, users with high algorithm literacy tend to diversify their information sources; they actively search for and compare information from different platforms and media [15,63]. This helps enhance users' sense of control over information seeking, reduces fatigue stemming from passive acceptance, and alleviates the feeling of helplessness induced by passively receiving

algorithmically recommended content.

Second, algorithm literacy acts as a "psychological buffer mechanism," reducing the sense of loss of control. For many users, algorithms constitute an opaque black box, with decision-making processes that are difficult to comprehend, leading to feelings of loss of control and distrust [64,65]. In contrast, users with high algorithm literacy possess a better understanding of the nature of algorithms. When users recognize that algorithms are not mysterious black boxes but are designed by humans for specific purposes, they feel a greater sense of control over the digital world [66]. Many users often hold high expectations for algorithms; when reality falls short of these expectations, such as when algorithm recommendations are poor or repetitive, disappointment and anxiety arise [20]. Users with high algorithm literacy have a more realistic perception of algorithmic limitations; they understand that algorithms are not infallible [15]. When users cease attributing limited knowledge acquisition solely to recommendation content homogenization, this realistic perception can effectively reduce the expectation gap, thereby diminishing the resulting negative emotions and anxiety [14].

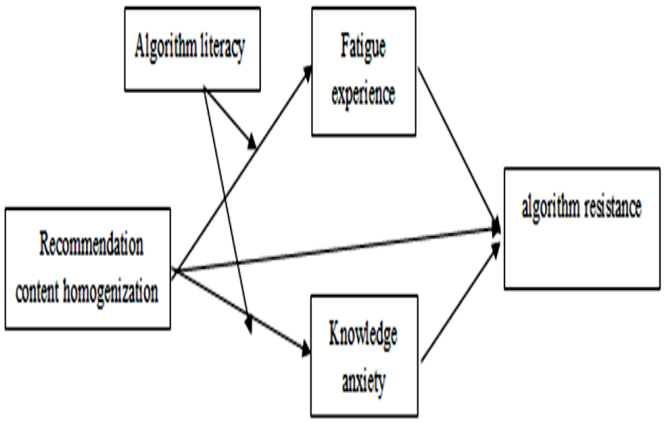
Third, algorithm literacy fosters critical thinking that counters "information bias diets," mitigating knowledge anxiety. Algorithm literacy encourages users to maintain a critical attitude towards algorithmically recommended content [15]. Users equipped with a high level of algorithm literacy are more aware that "not all recommended content is true." They no longer blindly trust recommendation results but instead question the reliability, fairness, and potential manipulation of information by algorithms[67]. Such critical thinking aids users in discerning false information and propaganda, thereby alleviating knowledge anxiety arising from information insularity [15]. Based on the above discussion, the following hypothesis is proposed:

H6: Algorithmic literacy negatively moderates the relationship between recommendation content homogenization and fatigue experience.

H7: Algorithm literacy negatively moderates the relationship between recommendation content homogenization and knowledge anxiety.

Based on the above analysis, the following theoretical models (Figure 1) are constructed in this study.

Figure 1 Theoretical model



Data Collection and Analysis

Sample selection and data source

This study utilizes online questionnaires survey method for data collection. College students, as primary users of platforms utilizing recommendation algorithms and being easily accessible for research, were selected as the primary survey respondents. The questionnaires were mainly distributed to college students through a professional survey platform (Credamo), and additionally, random distribution was conducted through platforms such as QQ and WeChat. Furthermore, the gathered information is strictly confidential and anonymous and is only used for academic research purposes. All participants have been informed consent before participating in the study. As of August 30, 2024, a total of 323 questionnaires were collected, with 22 invalid ones excluded, resulting in 301 valid questionnaires, yielding an effective response rate of 93.2%. Descriptive statistical data of the survey sample can be found in Table 1.

Table 1 Sample descriptive statistics

Variate	Type	Frequency	Percent (%)
Gender	Male	87	28.9
	Female	214	71.1
Age	Age 17 and under	4	1.3
	18-20 years old	130	43.2
	21-23 years old	141	46.8
	24-27 years old	20	6.6
	Age 28 and older	6	2
Graduate degree	Junior College	11	3.7
	Bachelor's Degree	260	86.4
	Master's Degree	23	7.6
	Doctoral Degree	7	2.3
Software usage time	More than 3 hours	126	41.9
	2-3 hours	94	31.2
	1-2 hours	47	15.6
	0.5-1 hour	30	10
	Less than 0.5 hours	4	1.3
Software usage frequency	Multiple times a day	237	78.7
	Once a day	40	13.3
	Less than ten times a week	21	7
	Less than ten times a month	3	1
	Less than ten times in six months	0	0
Software exposure time	5 years and above	168	55.8
	3-4 years	97	32.2
	2-3 years	34	11.3
	1 year	0	0
	Within half a year	2	0.7

Measures

The questionnaire consists of two parts: demographic analysis and core research construct measurement. In the demographic section, it includes age, gender, single App usage time, App usage frequency, and App exposure time. In the core research construct measurement section, all variables are adapted from established scales in mainstream domestic and international journals. All items are measured using a seven-point Likert scale ((ranging from 1 = "strongly disagree," to 7 = "strongly agree."

Recommendation content homogenization. The scale for recommendation content homogenization was adapted from the scale by Yu and Wang [68], and includes 5 items. An example item is "I always see content from the same group of bloggers, even though I haven't followed them" . The Cronbach's α coefficient is 0.825.

Fatigue experience. Fatigue experience was measured with 6 items developed by Zhang et al.[69], and includes. An

example item is "Using this app sometimes makes me feel exhausted" . The Cronbach's α coefficient is 0.878.

Knowledge anxiety. Knowledge anxiety was measured with 8 items developed by Sun et al. [70]. An example item is "I often feel anxious about my insufficient knowledge reserves and frequently visit online knowledge platforms" . The Cronbach's α coefficient is 0.915.

Algorithm resistance behavior. We measured algorithm resistance behavior with the 6-item scale adapted from Liao et al. [19]. An example item is "I will like content that I am not actually interested in." The Cronbach's α coefficient is 0.714.

Algorithm literacy. We measured algorithm literacy with the 9-item scale adapted from Yi Ming et al. [51]. An example item is "In the process of using the App, I know which of my needs need to be fulfilled through algorithms." The Cronbach's α coefficient is 0.970.

The Cronbach's α coefficients for all scales used in this study exceeded 0.7, indicating acceptable reliability of the measurement instruments.[71]

Common Method Biases

Due to the limitations of the data collection method, the five main variables of this study—recommendation content homogenization, fatigue experience, knowledge anxiety, algorithm resistance behavior, and algorithm literacy — were all derived from subjective self-reports by the subjects. This made the study potentially susceptible to common method bias, hence it is necessary to verify the issue of common method bias through statistical control. The Harman's single-factor test in this study primarily involves conducting an unrotated exploratory factor analysis on the five core variables of the study. The results showed that the first factor explains 32.462% of the variance, which was below the overall contribution of 50% and within an acceptable range, indicating that there was no common source bias issue.

Validity Testing

This study employs AMOS 24.0 to conduct confirmatory factor analysis to compare the fit indices of the research model and various competing models, in order to test the structural validity of the model in this study. As shown in Table 2, compared to other models, the baseline model (five-factor model) of this paper had the best fit indices (χ^2/df=2.429<3, RMSEA=0.069<0.08, CFI=0.905>0.9, TLI=0.896≈0.9) and was significantly superior to all alternative models, indicating that the five-factor model had a significant fit advantage, thus the structural validity of the model in this study was good.[72,73]

Table 2 Result of confirmatory factor analysis

Model	χ^2	df	X^2/df	RMSEA	CFI	TLI
Five-factor model	1248.634	514	2.429	0.069	0.905	0.896
Four-factor model	2080.511	521	3.993	0.100	0.798	0.782
Three-factor model	2541.39	524	4.85	0.113	0.739	0.720
Two-factor model	2607.167	526	4.957	0.115	0.730	0.712
Single-factor model	4641.349	527	8.807	0.161	0.467	0.433

Note: Five-factor model: ACSM;FATG;STRS;AGAV;AGLT
Four-factor model: ACSM+FATG;STRS;AGAV;AGLT
Three-factor model: ACSM+FATG+STRS;AGAV;AGLT
Two-factor model: ACSM+FATG+STRS+AGAV;AGLT
Single-factor model: ACSM+FATG+STRS+AGAV+AGLT

Descriptive Statistics Analysis

The means, standard deviations, and correlation coefficients of the variables in this study were shown in Table 3. The results indicated that recommendation content homogenization had a significant positive correlation with fatigue experience ($r = 0.258$, $p < 0.01$), a significant positive correlation with knowledge anxiety ($r = 0.320$, $p < 0.01$), and a significant positive correlation with algorithm resistance behavior ($r = 0.245$, $p < 0.01$). Fatigue experience had a significant positive correlation with algorithm resistance behavior ($r = 0.558$, $p < 0.01$), and knowledge anxiety also had a significant positive correlation with algorithm resistance behavior ($r = 0.593$, $p < 0.01$). The results were in line with the expected judgments, providing preliminary support for Hypotheses H1, H2, and H4, and offering initial validation for the hypotheses testing in this study.

Table 3 Mean, standard deviations, and correlations of variables

Variate	Mean	Standard deviations	Age	Gender	SUT	SUF	SET	ACSMM	FATGM	STRSM	AGAVM	AGLTM
Age	2.648	0.713	1									
Gender	1.711	0.454	-0.058	1								
SUT	1.977	1.047	-0.042	-0.056	1							
SUF	1.302	0.642	-0.087	-0.054	0.507**	1						
SET	1.575	0.743	-0.170**	0.01	0.064	0.075	1					
ACSMM	5.413	0.926	0.079	0.025	0.031	0.056	-0.172**	1				
FATGM	4.492	1.267	0.018	0.022	0.025	0.071	-0.063	0.258**	1			
STRSM	4.520	1.322	0.065	0.027	-0.101	-0.02	-0.065	0.320**	0.597**	1		
AGAVM	4.364	1.002	0.104	-0.034	0.028	0.009	-0.054	0.245**	0.558**	0.593**	1	
AGLTM	3.897	1.767	-0.046	0.026	0.002	-0.034	0.047	-0.154**	-0.306**	-0.310**	-0.310**	1

Note： SUT = Software usage time;
SUF = Software usage frequency;
SET = Software exposure time;
ACSMM = Recommendation content homogenization;
FATGM = Fatigue experience;
STRSM = Knowledge anxiety;
AGAVM = Algorithm resistance behavior;
** means $p < 0.01$

Hypotheses Testing

Direct Effect

To further examine the direct effects of recommendation content homogenization on algorithm resistance behavior, fatigue experience, and knowledge anxiety, respectively, this study utilized SPSS 22.0 for regression analysis, with the results presented in Table 4.

Table 4 Results of regression analysis

Variable	FATGM	STRSM	AGAVM		
	Model 1	Model 2	Model 3	Model 4	Model 5
Age	-0.012	0.018	0.079	0.091	0.071
Gender	0.031	0.02	0.016	-0.002	0.005
SUT	0.013	-0.118	0.055	0.051	0.126
SUF	0.043	0.044	-0.024	-0.039	-0.046
SET	-0.026	0.005	-0.015	-0.017	-0.27
ACSMM	0.248***	0.309***	0.234***		
FATGM				0.558***	
STRSM					0.595***

Note: SUT = Software usage time;
SUF = Software usage frequency;
SET = Software exposure time;
ACSMM = Recommendation content homogenization;
FATGM = Fatigue experience;
STRSM = Knowledge anxiety;
AGAVM = Algorithm resistance behavior;
*** $p < 0.001$
** $p < 0.01$

Firstly, to examine the direct relationships between the recommendation content homogenization and fatigue experience, knowledge anxiety, and algorithm resistance behavior, respectively, this study set recommendation content homogenization as the independent variable, and fatigue experience, knowledge anxiety, and algorithm resistance behavior as the dependent variables, incorporating them into Model 1, 2, and 3, respectively.

As shown in Table 4, recommendation content homogenization significantly and positively affected users' algorithm resistance behavior ($\beta = 0.234$, $p < 0.001$), supporting H1. Recommendation content homogenization significantly and positively affects users' fatigue experience ($\beta = 0.248$, $p < 0.001$), supporting H2. Additionally, recommendation content homogenization significantly and positively affected users' knowledge anxiety ($\beta = 0.309$, $p < 0.001$), supporting H4.

Furthermore, this study set users' fatigue experience and knowledge anxiety as independent variables, and algorithm resistance behavior as the dependent variable, incorporating algorithm resistance behavior into Models 4 and 5. The regression analysis results revealed that users' fatigue experience significantly and positively affects users' algorithm resistance behavior ($\beta = 0.558$, $p < 0.001$), preliminarily supporting H3 and providing support for the test of mediating effects. At the same time, knowledge anxiety significantly and positively affected algorithm resistance behavior ($\beta = 0.595$, $p < 0.001$), preliminarily supporting H5 and providing support for the test of mediating effects.

Mediation Effect

This study employed the Bootstrapping method to examine the mediating effects of two pathways. Following Hayes' recommendation 74, the mediating effect test with Bootstrapping was repeated 5,000 times, with age, gender, software usage time, and software exposure time as control variables. The sampling number was set to 5,000 times, and the confidence level was 95%. The results were shown in Table 5. The results indicate that the mediating effect value of fatigue experience was 0.0817, with a 95% confidence interval of [0.0370, 0.1337]. The confidence interval did not include 0, which suggested that the mediating effect of fatigue experience between the recommendation content homogenization and algorithm resistance behavior was significant, and Hypothesis 3 was established. The mediating effect value of knowledge anxiety was 0.1333, with a 95% confidence interval of [0.0700, 0.2053]. The confidence interval did not include 0, which indicated that the mediating effect of knowledge anxiety between the App recommendation content homogenization and algorithm resistance behavior was significant, supporting Hypothesis 5. Among the two mediating pathways, the mediating effect of knowledge anxiety was higher, accounting for 62%; the mediating effect of fatigue experience was lower, accounting for 38%.

Table 5 Results of mediation effect test

Path	Total Effect		Direct effect		Indirect Effect		
	β	T	β	T	β	LLCI	ULCI
ACSM->FATG->AGAV	0.2529	4.0455	0.0379	0.731	0.0817	0.037	0.1337
ACSM->STRS->AGAV					0.1333	0.07	0.2053

Note: ACSMM = Recommendation content homogenization;
FATGM = Fatigue experience;
STRSM = Knowledge anxiety;
AGAV = Algorithm resistance behavior

This study employed the Bootstrapping method with 5,000 resamples to further test the moderating role of algorithmic literacy on the relationships between the recommendation content homogenization and fatigue experience, as well as knowledge anxiety. The results were shown in Table 6. The results indicated that the regression coefficient of the recommendation content homogenization on fatigue experience was significantly positive (β = 1.7369, 95% confidence interval [1.4248, 2.0544], p < 0.001), and the interaction term between the recommendation content homogenization and algorithm literacy had significantly negative regression coefficient on fatigue experience (β = -0.4170, 95% confidence interval [-0.4993, -0.3348], p < 0.001), suggesting that algorithm literacy negatively moderated the positive correlation between the recommendation content homogenization and fatigue experience. Similarly, the regression coefficient of the recommendation content homogenization on knowledge anxiety was significantly positive (β = 1.5870, 95% confidence interval [1.2412, 1.9327], p < 0.001), and the interaction term between the recommendation content homogenization and algorithm literacy had a significantly negative regression coefficient on knowledge anxiety (β = -0.3433, 95% confidence interval [-0.4336, -0.2530], p < 0.001), indicating that algorithm literacy negatively moderates the positive correlation between the recommendation content homogenization and algorithm resistance behavior. Combining the above results, algorithmic literacy significantly negatively moderated the positive correlations between the recommendation content homogenization and fatigue experience, as well as knowledge anxiety, validating research hypotheses H6 and H7.

Table 6 Result of moderation effect test

Types of variables	Variables	Dependent Variable : FATG	Dependent Variable : STRS		
		M1	M2		
		β	95%CI	β	95%CI
CV	Age	-0.1603	[-0.3514,0.0307]	-0.0849	[-0.2947,0.1249]
	Gender	0.1296	[-0.1421,0.4014]	0.0811	[-0.2174,0.3769]
	SUT	0.0353	[-0.0957,0.1663]	-0.1313	[-0.2752,0.0125]
	SUF	0.0475	[-0.1677,0.2626]	0.0566	[-0.1797,0.2928]
	SET	-0.0722	[-0.2377,0.0934]	-0.0112	[-0.1930,0.1706]
IV	ACSMM	1.7396	[1.4248,2.0544]	1.5870	[1.2412,1.9327]
	AGLTM	2.2401	[1.7540,2.7263]	1.8167	[1.2828,2.3507]
Interactions	ACSMM*AGLTM	-0.4170	[-0.4993,-0.3348]	-0.3433	[-0.4336,-0.2530]

Note: SUT = Software usage time;
SUF = Software usage frequency;
SET = Software exposure time;
CV = Control variables;
IV = Independent Variables;
ACSMM = Recommendation content homogenization;
FATGM = Fatigue experience;
STRSM = Knowledge anxiety;
AGLTM = Algorithm literacy

Research Conclusion and Discussion

Research Findings

In the 1990s, to address the search difficulties caused by the vast amount of information on the Internet, Page et al. proposed the PageRank algorithm to rank web page search results [75]. With the help of this algorithm, Google's search engine achieved great success. With the rise of mobile internet and the emergence of self-media content creation, the volume of data online has surged even further, rendering traditional algorithms insufficient to meet users' demands.

In order to provide users with the content they need to gain an advantage in fierce market competition, many applications have gradually begun to use artificial intelligence-driven interactive content distribution models to deliver personalized content to users, thereby improving user experience and enhancing user stickiness. However, the similarity of algorithmically recommended content has triggered resistance behaviors against algorithms, leading to a decline in the experience of using Apps. Therefore, exploring the influencing mechanisms behind algorithm resistance behaviors and identifying potential solutions is of significant theoretical and practical importance.

This study organized and summarizes existing literature and conducted online questionnare surveys to investigate the mechanism by which the recommendation content homogenization affects user algorithmic resistance behavior from the perspective of conservation of resources Theory. Findings show that recommendation content homogenization significantly promotes the emergence of algorithm resistance behavior, with fatigue experience and knowledge anxiety both playing significant mediating roles.Notably, the mediating effect of knowledge anxiety is found to be significantly greater than that of fatigue experience, indicating that users' knowledge anxiety is more likely to trigger algorithmic resistance behavior than the fatigue experience caused by content homogenization. College students are at a critical stage of knowledge accumulation, skill development, and future career planning. In this context, while fatigue experience induced by content homogenization is prevalent among them, the "fear of missing out" (FOMO) and sense of falling behind stemming from hindered knowledge acquisition due to this homogeneity — which directly fuels knowledge anxiety — may prove more intense and enduring. Furthermore, the study also finds that the direct impacts of the recommendation content homogenization on users' fatigue experience and knowledge anxiety are both moderated by algorithmic literacy. That is, the higher the level of algorithm literacy, the weaker the promoting effect of recommendation content homogenization on users' fatigue experience, and vice versa, the promoting effect of recommendation content homogenization on fatigue experience will be enhanced. At the same time, the higher the level of algorithm literacy, the weaker the positive impact of the recommendation content homogenization on knowledge anxiety, and the lower the level of algorithmic literacy, the stronger the positive impact of the recommendation content homogenization on knowledge anxiety.

Theoretical Implications

Our paper makes several contributions. Firstly, this study introduces the concept of algorithmic resistance behavior into the field of user behavior research, expanding the study of the impact of App content homogenization on user behavior. Previous research on recommendation content homogenization has predominantly focused on its impact on the formation of users' information cocoons, filter bubbles, and echo chamber effects. Limited attention has been paid to its influence on user behaviors, particularly regarding specialized investigations into college student populations. The study by Liang et al. (2023) discussed users' "algorithm resistance" and "avoidance" behaviors in response to information narrowness and redundancy within homogenized information flows, situating these behaviors within a stress-coping framework [20]. Meanwhile, Liao et al. (2023) examined the impact of content similarity in app push notifications on disingenuous interactions and app usage intention from a coping behavior perspective[19]. Additionally, Lv et al. (2022) explored adolescents' willingness and behaviors related to algorithm resistance in the context of short-video applications [32]. Building upon these studies, the current research conceptualizes algorithm resistance as an active user-initiated behavior aimed at counteracting algorithmic erosion of their resources or negative influences, thereby further refining this concept. It is not merely passive avoidance but may also encompass proactive strategic adjustments, such as modifying usage habits or seeking diverse information sources. This study aims to analyze the influence and mechanisms by which recommendation content homogenization affects algorithm resistance behavior from the user's perspective, integrating both emotional and cognitive viewpoints to construct a two-mediation pathway— fatigue experience and knowledge anxiety. This represents a deepening and

expansion of existing research and helps to promote a comprehensive understanding of the relationship between Apps algorithmic recommendations and user behaviors.

Secondly, this study promotes the application research of conservation of resources (COR) theory by revealing the internal psychological mechanisms through which the recommendation content homogenization affects algorithm resistance behavior. COR theory is a motivational theory that explains the causes of behavior in terms of an individual's resource stock and its dynamic changes, suggesting that people are always actively striving to maintain, protect, and build the resources they value. Scholars have applied COR theory to organizational behavior research [76], using the theory to analyze the impact of resources on individual behavior under stress. Based on conservation of resources (COR) theory, this paper proposes that, for users, recommendation content homogenization leads to the loss of resources. To cope with the loss of these resources, users will engage in algorithm resistance behaviors. Differing from traditional organizational contexts, this study extends the application scenario of COR to algorithmic platforms. Furthermore, this study incorporates abstract resources—emotional resources and cognitive diversity resources—into the COR resource taxonomy, revealing the invisible deprivation of users' psychological resources by algorithmic control. This exploration sheds light on the "black box" connecting algorithmic recommendation content homogenization to user algorithm resistance behavior, thereby expanding the application of COR theory.

Finally, this study identifies algorithm literacy as a moderating variable that mitigates the impact of the recommendation content homogenization on fatigue experience and knowledge anxiety. Previous studie has shown that content type can serve as a moderating variable[19], affecting the impact of app content similarity on fatigue experience, which in turn affects misrepresentation interactions behavior. This study, from the perspective of users' cognitive level, proposes and verifies that algorithm literacy has a moderating effect on two variables: knowledge anxiety and fatigue experience. Unlike previous studies that focused on external factors such as content attributes influencing users' fatigue experience, this research reveals the moderating role of users' intrinsic cognition (algorithm literacy). This finding enriches the psychological mechanism model between recommendation content homogenization and users' algorithm resistance, suggesting that users' proactive cognitive and comprehension abilities are also critical factors affecting their experience, thereby providing new insights for subsequent related research.

Managerial implications

On the content platform side, on the one hand, platforms should reduce the degree of recommendation content homogenization to mitigate user algorithm resistance and enhance user experience. Existing research on algorithmic recommendation systems primarily focuses on recommendation accuracy and user click-through rates. However, when developing algorithms, content platforms should also introduce and optimize metrics for evaluating content diversity to decrease the homogenization of recommended content. This implies that algorithm designers should not rely solely on user behavioral data (such as clicks and dwell time), but also pay attention to the breadth and novelty of content. For instance, knowledge graph technology can be employed to enhance the diversity and relevance of recommended content [77]. On the other hand, content platforms can design more intuitive and user-friendly tools to help users understand the recommendation logic and grant users' greater control over the recommended content. Examples include features explaining "why you are seeing this recommendation" or refined "not interested" options. By enhancing user algorithm literacy and mitigating fatigue experience, these measures can help reduce user algorithm resistance.

In the field of education and training, schools, media, and government agencies can develop relevant curricula and public awareness campaigns to enhance users' algorithm literacy—particularly among vulnerable groups such as adolescents and the elderly—by strengthening their understanding of algorithmic operations (e.g., perception and recommendation mechanisms) and cultivating critical thinking skills. Improving algorithm literacy not only helps users comprehend the intrinsic logic of algorithmic

recommendations, thereby alleviating knowledge anxiety when confronted with recommendation content homogenization; more importantly, it empowers users to navigate algorithms. Although algorithmic principles are often regarded as "black boxes," users with algorithm literacy can guide recommendation directions through proactive choices (e.g., liking, blocking, adjusting interest tags). Such guidance not only aligns recommended content more closely with genuine individual needs but also effectively mitigates excessive content homogenization, thereby reducing resultant negative emotional experiences.

Limitation of Study

As an exploratory study, this paper inevitably has limitations and areas that warrant further in-depth research. First, algorithm resistance behavior, as a reaction of users to the recommendation content homogenization when using Apps, has potential connections with many psychological factors and objective conditions, and there are still many psychological factors that could serve as mediators. This paper, based on relevant literature, examines the mediating roles of fatigue experience and knowledge anxiety between recommendation content homogenization and algorithm resistance behavior. Although the empirical results have supported our initial hypotheses, there may be other processes that mediate the effects of App recommendation content homogenization on algorithm resistance behavior. Future research should investigate the mechanisms and empirical links between the two from various perspectives, such as privacy concerns and technological control. Secondly, while this study confirmed the absence of common method bias using Harman's single-factor method, the data were derived from participants' simultaneous self-report, which were inevitably influenced by individual subjective factors. Future studies could adopt multi-time point pairing data or longitudinal designs to further enhance the rigor of the conclusions. Third, this study did not account for certain covariates that may influence algorithmic resistance behavior, such as content types (e.g., shopping, lifestyle, science popularization) and presentation formats (e.g., images and text, short videos, long videos). Future research can conduct a more comprehensive discussion on these aspects.

References:

1. Le Chengyi, Wang Zixin & Kong Weiwei. Algorithm Appreciation vs. Algorithm Aversion: (2024). The User "Algorithm Paradox" in Short Video Intelligent Recommendation. Information Magazine 43, 170-181
2. Le Chengyi, Wang Zixin, Zhang Jinping & Cheng Jiahui (2025).. Research on User Algorithm Response to Intelligent Recommendation on Short Video Platforms. Library Construction, 1-28
3. Liu, Yutong; Wang, Xiwei; Wang, Nan, Axue & Wujisguleng. (2024). A Study on Algorithmic Resistance Behavior of Social Media Information Dissemination under Major Public Health Emergencies. Library and Information Service, 68, 98-109 https://doi.org/10.13266/j.issn.0252-3116.2024.09.010
4. Hong Jiewen & Chen Rongwei (2022).. Consciousness stimulation and rule imagination: Tactical dependence and practical path of user resistance to algorithms. Journalism and Communication Research 29, 38-56+126-127
5. Zhao Sikong (2021). An Exploration of Algorithmic Ontology and Its Critique. Studies in Dialectics of Nature, 37, 52-58. https://doi.org/10.19484/j.cnki.1000-8934.2021.06.010
6. Karizat, N., Delmonaco, D., Eslami, M. & Andalibi, N. Algorithmic Folk Theories and Identity: How TikTok Users Co-Produce Knowledge of Identity and Engage in Algorithmic Resistance. *Proceedings of the ACM on Human-Computer Interaction* **5**, 1-44 (2021). https://doi.org/10.1145/3476046
7. Li, T., Dong, Y. & Zhang, B. in *2023 8th International Conference on Information Systems Engineering (ICISE)*. 286-289.
8. Eg, R., Demirkol Tønnesen, Ö. & Tennfjord, M. K. A scoping review of personalized user experiences on social media: The interplay between algorithms and human factors. *Computers in Human Behavior Reports* **9**, 100253 (2023). https://doi.org/https://doi.org/10.1016/j.chbr.2022.100253

9. Hardy, G. E., Shapiro, D. A. & Borrill, C. S. Fatigue in the workforce of national health service trusts: Levels of symptomatology and links with minor psychiatric disorder, demographic, occupational and work role factors. *Journal of Psychosomatic Research* **43**, 83-92 (1997). https://doi.org/10.1016/s0022-3999(97)00019-6
10. Dhir, A., Kaur, P., Chen, S. & Pallesen, S. Antecedents and consequences of social media fatigue. *International Journal of Information Management* **48**, 193-202 (2019).
11. Zhao Sikong (2021). An Exploration of Algorithmic Ontology and Its Critique. Studies in Dialectics of Nature, 37, 52-58.
12. Chen, Lanjie; Wu, Lanbing & Xu, Fang (2025). Research on Information Anxiety: A Systematic Analysis of Manifestations, Causes, Consequences and Interventions. Digital Library Forum 21, 50-60.
13. Dogruel, L., Masur, P. & Joeckel, S. Development and Validation of an Algorithm Literacy Scale for Internet Users. *Communication Methods and Measures* **16**, 115-133 (2021). https://doi.org/10.1080/ 19312458. 2021.1968361
14. Yang, H., Li, D. & Hu, P. Decoding algorithm fatigue: The role of algorithmic literacy, information cocoons, and algorithmic opacity. *Technology in Society* **79**, 102749 (2024). https://doi.org/10.1016/ j.techsoc.2024.102749
15. Frau-Meigs, D. Algorithm Literacy as a Subset of Media and Information Literacy: Competences and Design Considerations. *Digital* **4**, 512-528 (2024). https://doi.org/10.3390/digital4020026
16. Ming, F., Tan, L. & Cheng, X. Hybrid Recommendation Scheme Based on Deep Learning. *Mathematical Problems in Engineering* **2021**, 1-12 (2021). https://doi.org/10.1155/2021/6120068
17. Liu, Z. & Ren, F. Algorithm Improvement of Movie Recommendation System based on Hybrid Recommendation Algorithm. *Frontiers in Computing and Intelligent Systems* **3**, 113-117 (2023). https://doi.org/10.54097/fcis.v3i3.8581
18. Jin, Z., Ye, F., Nedjah, N. & Zhang, X. A comparative study of various recommendation algorithms based on E-commerce big data. *Electronic Commerce Research and Applications* **68**, 101461 (2024). https://doi.org/10.1016/j.elerap.2024.101461
19. Liao, Miyan; Fang, Jiaming; Yang, Jingjing & Hossin, M. A. (2023) The impact of algorithm-recommended content similarity on app usage from a behavioral perspective. Nankai Management Review 26, 178-190.
20. Zhang, L., Bi, W., Zhang, N. & He, L. Coping with Homogeneous Information Flow in Recommender Systems: Algorithmic Resistance and Avoidance. *International Journal of Human–Computer Interaction* **40**, 6899-6912 (2023). https://doi.org/10.1080/ 10447318.2023.2267931
21. Anwar, M. S., Schoenebeck, G. & Dhillon, P. S. Filter Bubble or Homogenization? Disentangling the Long-Term Effects of Recommendations on User Consumption Patterns. *arXiv e-prints*, arXiv: 2402.15013 (2024). https://doi.org/10.48550/ARXIV.2402.1501
22. De Biasio, A., Monaro, M., Oneto, L., Ballan, L. & Navarin, N. On the problem of recommendation for sensitive users and influential items: Simultaneously maintaining interest and diversity. *Knowledge-Based Systems* **275**, 110699 (2023). https://doi.org/10.1016/ j.knosys.2023.110699
23. Zhang, L., Lian, Y., Wu, H., Song, C. & Yuan, X. An Exploratory Study on Information Cocoon in Recommender Systems. *Data Science and Engineering* (2025). https://doi.org/10.1007/s41019-025-00288-9
24. Liu, P., Shivaram, K., Culotta, A., Shapiro, M. A. & Bilgic, M. The Interaction between Political Typology and Filter Bubbles in News Recommendation Algorithms. *Proceedings of the Web Conference 2021*, 3791-3801 (2021). https://doi.org/10.1145/ 3442381.3450113
25. Tianyi Zhou, Y. Z. Y. Z. On the Relationship among User's Reading Behavior, Algorithm Recommendation Mechanism and the Manufactured Filter Bubbles Effect. *CONVERTER*, 730-744 (2021).

https://doi.org/10.17762/converter.107

26. Pathak, R., Spezzano, F. & Pera, M. S. Understanding the Contribution of Recommendation Algorithms on Misinformation Recommendation and Misinformation Dissemination on Social Networks. *ACM Transactions on the Web* **17**, 1-26 (2023). https://doi.org/10.1145/3616088
27. Chen, L., Sun, R., Yuan, Y. & Zhan, X. The influence of recommendation algorithm's information flow on targeted advertising audience's coping behavior. *Acta Psychologica* **243**, 104168 (2024). https://doi.org/10.1016/j.actpsy.2024.104168
28. Yang, J., Li, H., Zhang, L. & Xu, G. Coping Responses to the Stress of Using News Platforms' Recommendation Algorithms. *International Journal of Human–Computer Interaction* **41**, 4759-4774 (2024). https://doi.org/10.1080/10447318.2024.2352937
29. Festinger, L. & Carlsmith, J. M. Cognitive consequences of forced compliance. *The Journal of Abnormal and Social Psychology* **58**, 203-210 (1959). https://doi.org/10.1037/h0041593
30. Marikyan, D., Papagiannidis, S. & Alamanos, E. Cognitive Dissonance in Technology Adoption: A Study of Smart Home Users. *Information Systems Frontiers* **25**, 1101-1123 (2020). https://doi.org/10.1007/s10796-020-10042-3
31. Lv, X., Li, J. & Wang, Q. The Dark Side of Recommendation Algorithms in Chinese Mass Short Video Apps: Effect of Perceived Over-Recommendation on Users' Cognitive Dissonance and Discontinuance Intention. *International Journal of Human–Computer Interaction* **41**, 6701-6715 (2024). https://doi.org/10.1080/10447318.2024.2383038
32. Lv, X., Chen, Y. & Guo, W. Adolescents' Algorithmic Resistance to Short Video APP's Recommendation: The Dual Mediating Role of Resistance Willingness and Resistance Intention. *Frontiers in Psychology* **13** (2022). https://doi.org/10.3389/fpsyg.2022.859597
33. Fu, H. & Sun, Y. Unravelling the algorithm manipulation behavior of social media users: A configurational perspective. *null* (2024).
34. Cen, S. H., Ilyas, A., Allen, J., Li, H. & Madry, A. Measuring Strategization in Recommendation: Users Adapt Their Behavior to Shape Future Content. *undefined* (2024). https://doi.org/10.48550/ARXIV.2405.05596
35. Chen, Y. & Huang, J. Effective Content Recommendation in New Media: Leveraging Algorithmic Approaches. *IEEE Access* **12**, 90561-90570 (2024). https://doi.org/10.1109/access.2024.3421566
36. Goswami, A. Recommendation System as a Social Determinant of Health. *Digital Society* **3** (2024). https://doi.org/10.1007/s44206-024-00118-x
37. Liu, Y. *et al.* Diversified Interactive Recommendation with Implicit Feedback. *Proceedings of the AAAI Conference on Artificial Intelligence* **34**, 4932-4939 (2020).
38. Ma, H., Liu, X. & Shen, Z. User Fatigue in Online News Recommendation. *Proceedings of the 25th International Conference on World Wide Web*, 1363-1372 (2016). https://doi.org/10.1145/2872427.2874813
39. Gao, C. *et al.* CIRS: Bursting Filter Bubbles by Counterfactual Interactive Recommender System. *ACM Transactions on Information Systems* **42**, 1-27 (2023). https://doi.org/10.1145/3594871
40. Lin, H.-F. Determinants of successful virtual communities: Contributions from system characteristics and social factors. *Information & Management* **45**, 522-527 (2008). https://doi.org/https://doi.org/10.1016/j.im.2008.08.002
41. Liu, Luchuan; Li, Xu & Zhang, Bingqian (2018). A review of research on negative emotions and passive usage behaviors of social media users. Journal of Information, 37, 105-113+121.
42. Li, N. *et al.* Modeling User Fatigue for Sequential Recommendation. *arXiv* (2024). https://doi.org/10.48550/ARXIV.2405.11764
43. Cheng, X. & Peng, G. Study on the Behavioral Motives

of Algorithmic Avoidance in Intelligent Recommendation Systems. *Journal of Global Information Management* **32**, 1-22 (2024). https://doi.org/10.4018/jgim.352857

44. Shan, W., Qiao, T. & Zhang, M. Getting more resources for better performance: The effect of user-owned resources on the value of user-generated content. *Technological Forecasting and Social Change* **161**, 120318 (2020). https://doi.org/10.1016/j.techfore.2020.120318
45. Duan Jinyun, Yang Jing & Zhu Yuelong. Resource conservation theories: content, theoretical comparison and research prospects. Psychological Research 13, 49-57 (2020).
46. Hobfoll, S. E., Halbesleben, J., Neveu, J.-P. & Westman, M. Conservation of Resources in the Organizational Context: The Reality of Resources and Their Consequences. *Annual Review of Organizational Psychology and Organizational Behavior* **5**, 103-128 (2018). https://doi.org/https://doi.org/10.1146/annurev-orgpsych-032117-104640
47. Yan, J. R. & Min, Y. User Fatigue in Interactive Evolutionary Computation. *Applied Mechanics and Materials*, 1333-1336 (2011). https://doi.org/10.4028/www.scientific.net/amm.48-49.1333
48. Tingwei, Z., Qinyu, Z., Defeng, S. & Ye, C. Research on User Behaviors and Their Forming Mechanism under Filter Bubbles. *null* (2023).
49. Qiao, R., Liu, C. & Xu, J. Making algorithmic app use a virtuous cycle: Influence of user gratification and fatigue on algorithmic app dependence. *Humanities and Social Sciences Communications* **11** (2024). https://doi.org/10.1057/s41599-024-03221-z
50. Zhang, K., Xie, Y., He, Y. & Wang, J. Emotional influences on user continuous use intention in recommended news apps: A study of algorithm appreciation and fatigue within the cognition-affect-conation framework. *Acta Psychologica* **256**, 105002 (2025). https://doi.org/10.1016/j.actpsy.2025.105002
51. Yi Ming, Fu Hang & Liu Jiyue (2023). A Study on App Users' Continued Use Willingness Based on Coping Theory in the Context of Information Cocoons. Intelligence and Information Work 44, 66-76.
52. Bekker, H. L., Legare, F., Stacey, D., O'Connor, A. & Lemyre, L. Is anxiety a suitable measure of decision aid effectiveness: a systematic review? *Patient Education and Counseling* **50**, 255-262 (2003). https://doi.org/https://doi.org/10.1016/S0738-3991(03)00045-4
53. Kuang Wenbo. (2019) Why does "knowledge anxiety" arise? People's Forum, 127-129.
54. Li Wu, Cui Jiayong & Zhou Li. (2022) Does paid knowledge service help alleviate knowledge anxiety? Empirical evidence from a mixed study. Library and Information Science 39, 103-115. https://doi.org/10.13366/j.dik.2022.03.103
55. Wang, S., Bozhi & Yuyi. Research on Accurate Recommendation of Learning Resources based on Graph Neural Networks and Convolutional Algorithms. *International Journal of Computer and Communication Technology*, 54-60 (2022). https://doi.org/10.47893/ijcct.2022.1448
56. Liu, Y. e. Research on Deep Learning-Based Algorithm and Model for Personalized Recommendation of Resources. *Journal of Physics: Conference Series* **2146**, 12007 (2022). https://doi.org/10.1088/1742-6596/2146/1/012007
57. Wu, X., Li, S., Leng, H. & He, Z. The Influence and Solution of College Students' "Information Cocoon" Effect. *International Journal of Education and Humanities* **6**, 171-172 (2022). https://doi.org/10.54097/ijeh.v6i2.3679
58. Sun, Y., Wu, Y. & Zhou, Y. Exploring the Influencing Factors of Breaking Through the Information Cocoon. *Communications in Humanities Research* **12**, 197-207 (2023). https://doi.org/10.54254/2753-7064/12/20230106
59. Zhang, Y. & Liu, J. Falling behind again? Characterizing and assessing older adults' algorithm literacy in interactions with video recommendations. *Journal of the Association for Information Science and*

Technology **76**, 604-620 (2024). https://doi.org/10.1002/asi.24960

60. Gagrčin, E., Naab, T. K. & Grub, M. F. Algorithmic media use and algorithm literacy: An integrative literature review. *New Media & Society* (2024). https://doi.org/10.1177/14614448241291137
61. Boots, B. C., Matlack, A. K. & Richardson-Gool, T. S. A Call for Promoting Algorithmic Literacy. *SSRN Electronic Journal* (2024). https://doi.org/10.2139/ssrn.4912427
62. Silva, D. E., Chen, C. & Zhu, Y. Facets of algorithmic literacy: Information, experience, and individual factors predict attitudes toward algorithmic systems. *New Media & Society* **26**, 2992-3017 (2022). https://doi.org/10.1177/14614448221098042
63. Barragán-Perea, E. A. & Tarango, J. Internet search algorithms: use of metadata, literacy and algorithmic education in the human–computer interaction. *Digital Library Perspectives* **40**, 404-415 (2024). https://doi.org/10.1108/dlp-01-2024-0009
64. Chen, C. How consumers respond to service failures caused by algorithmic mistakes: The role of algorithmic interpretability. *Journal of Business Research* **176**, 114610 (2024). https://doi.org/10.1016/j.jbusres.2024.114610
65. Shin, D. User Perceptions of Algorithmic Decisions in the Personalized AI System:Perceptual Evaluation of Fairness, Accountability, Transparency, and Explainability. *Journal of Broadcasting & Electronic Media* **64**, 541-565 (2020). https://doi.org/10.1080/08838151.2020.1843357
66. Ananny, M. & Crawford, K. Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability. *New Media & Society* **20**, 973-989 (2016). https://doi.org/10.1177/1461444816676645
67. Shin, D. How do people judge the credibility of algorithmic sources? *AI & SOCIETY* **37**, 81-96 (2021). https://doi.org/10.1007/s00146-021-01158-4
68. Yu Xin & Wang Jinpeng (2022). Re-understanding the "Information Cocoon": A Study on the Symbiotic Mechanism of Instrumental Rationality and Value Rationality in the Era of Intelligent Media. Journalism and Writing, 65-78..
69. Zhang, S., Zhao, L., Lu, Y. & Yang, J. Do you get tired of socializing? An empirical explanation of discontinuous usage behaviour in social network services. *Information & Management* **53**, 904-914 (2016).
70. Sun Jinhua, He Miao & Hu Jian. (2021) The Influence of Knowledge Anxiety on Platform Users' Willingness to Pay for Knowledge from the Perceived Value Perspective. Modern Information 41, 129-138.
71. Nunnally, J. C. & Bernstein, I. H. *Psychometric Theory*. 3rd edn, (McGraw-Hill, Inc., 1994).
72. Johanson, G. A. & Brooks, G. P. Initial Scale Development: Sample Size for Pilot Studies. *Educational and Psychological Measurement* **70**, 394-400 (2009). https://doi.org/10.1177/0013164409355692
73. Hu, L. t. & Bentler, P. M. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal* **6**, 1-55 (1999). https://doi.org/10.1080/10705519909540118
74. Hayes, A. F. Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. *Communication monographs* **76**, 408-420 (2009).
75. Page, L. The PageRank citation ranking: Bringing order to the web. (Technical Report, 1999).
76. Liao Huahua, Huang Lei & Hu Bin. (2022) Application of resource conservation theory in organizational behavior: evolution and challenges. Advances in Psychological Science 30, 449-463.
77. He, Q. & Liu, S. Optimization of Recommendation Algorithm Based on Knowledge Graph. *2022 4th International Conference on Applied Machine Learning (ICAML)*, 133-136 (2022). https://doi.org/10.1109/icaml57167.2022.00032