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Decoding Information Fatigue in Recommender Systems: Insights from PLS-SEM, fsQCA, and cIPMA

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Abstract

This study develops an integrated framework to examine how algorithmic recommendation features (i.e., accuracy, transparency, and novelty) influence users' information fatigue via information narrowing and information overload on social media platforms. Drawing on survey data from 463 users, the study employed PLS-SEM to test variable relationships, cIPMA to assess importance–performance priorities, and fsQCA to identify configurational patterns. Findings reveal that excessive accuracy intensifies information narrowing and subsequently increases fatigue, whereas novelty significantly alleviates users' cognitive burden. Both information narrowing and information overload strongly drive information fatigue, while accuracy and transparency influence it indirectly. The cIPMA underscores information narrowing and novelty as the highest-priority areas for algorithmic optimization, and fsQCA identifies multiple distinct paths to low information fatigue, prominently featuring the presence of novelty and the absence of information overload as core conditions. The study advances the theoretical understanding of the psychological impacts of algorithmic recommendations and offers actionable insights for platforms to balance relevance with diversity and design user-controllable systems to mitigate information fatigue.

1. Introduction

With the continuous evolution of digital platform ecosystems, algorithmic recommendation systems have become the primary channel for users to access information. (Berk et al., 2023). Consequently, users' information acquisition methods are undergoing a profound shift from “active search” to “passive reception”. While algorithmic systems significantly enhance the efficiency of information distribution and user engagement, their pervasive application has inadvertently triggered an unavoidable "dark side". A critical manifestation of this is information fatigue-a state of psychological exhaustion and cognitive overload experienced when individuals are exposed to high-density, highly homogeneous, and redundant algorithmic feeds over an extended period (Shulman et al.,2021;Sheng et al.,2023). The consequences of information fatigue are not only manifested in reduced usage frequency, content resistance, and avoidance, but may also evolve into aversion to algorithmic recommendation systems, or even platform migration. This poses a significant challenge to the construction of a healthy platform ecosystem and sustainable user engagement (Pang et al., 2021; Oghuma et al., 2016; Shi et al., 2022). In recent years, the majority of digital users have spent most of their time on social media, with some even becoming addicted to it (Liu et al., 2021). However, once they become aware of their addiction, users often experience fatigue from the information recommended by social media. Many users begin to exhibit resistance and exhaustion, and user attrition has gradually become a significant challenge faced by various social platforms. As a result, the phenomenon of information fatigue induced by algorithmic recommendations is gradually emerging as a critical issue in the field of social media.

The consequences of information fatigue are detrimental and multidimensional. Behaviorally, it manifests not only in reduced usage frequency and lurking, but also extends to negative interactions (such as deliberately withholding likes or comments), ultimately escalating into psychological reactance,

algorithmic resistance, and platform migration(Zhang et al; Huang et al.,2020). Psychologically, prolonged exposure to information fatigue can severely impair users' mental well-being, triggering anxiety, depression, and profound emotional exhaustion. (Cheng et al., 2023; Ma et al., 2021) For social network services (SNS) providers, this fatigue-induced withdrawal breeds deep-seated distrust toward the platform and generates negative word-of-mouth (WOM). As users reduce their engagement or abandon the platform, it poses a severe threat to the advertising revenue, sustainable growth, and economic viability of the digital ecosystem. Therefore, understanding the mechanism of information fatigue induced by algorithmic recommendations has emerged as a critical imperative in information systems research.

Previous studies have explored the antecedents of information fatigue from various perspectives, confirming that algorithmic recommendation features significantly contribute to users' psychological burden and subsequent resistance(Liu et al.,2021). Specifically, excessive homogeneous content traps users in “filter bubbles” and “information cocoons,” which narrows their information scope and induces exhaustion (Zhang et al.,2024).Others have approached the issue from the perspective of information overload and privacy concerns, arguing that the relentless push of algorithm-driven content significantly increases users’cognitive load and privacy anxiety, thereby fostering resistance and avoidance behaviors(Can et al.,2024).

However, in digital platforms, research combining partial least squares structural equation modeling (PLS-SEM) based on sufficiency logic, fuzzy-set qualitative comparative analysis (fsQCA) based on configurational logic, and combined importance-performance map analysis (cIPMA) to explore the relationship between algorithmic recommendation features and information fatigue remains insufficient. This is particularly important in digital platform ecosystems, because the interactions of various algorithmic features may yield entirely different outcomes due to intense human-algorithm interactivity, severe information homogeneity, and users' cognitive limitations.

To address this gap in the literature, this study is grounded in user appraisal theory and employs a mixed-methods approach combining PLS-SEM, fsQCA, and cIPMA to reveal the complex causal mechanisms of algorithmic fatigue and identify critical thresholds and priority intervention models for alleviating user resistance. Specifically, PLS-SEM is utilized to confirm the net effects and driving mechanisms of algorithmic stressors on fatigue (sufficiency logic); fsQCA is applied to uncover the asymmetric configurational recipes that trigger high user resistance (causal complexity) and cIPMA is adopted to quantify the specific performance thresholds and identify the most urgent bottlenecks for platform intervention.

Driven by this integrated framework, this study seeks to address the following research questions:

RQ1: How do algorithmic recommendation features linearly influence information fatigue?

RQ2: What are the asymmetric configurational recipes of algorithmic features that lead to high user resistance?

RQ3: What are the critical performance thresholds and priority intervention paths to effectively mitigate user resistance?

This study investigates the impact of algorithmic recommendation features on information fatigue within digital platforms, with a specific focus on the mediating effects of information overload and information narrowing. By adopting a robust mixed-methods approach that integrates partial least squares structural equation modeling (PLS-SEM), fuzzy-set qualitative comparative analysis (fsQCA) and combined importance-performance map analysis (cIPMA),this research provides a more comprehensive understanding of user resistance to algorithmic recommendation systems.

First, compared to previous studies that often examined algorithmic features and user psychology in isolation, this study demonstrates theoretical superiority by constructing a more comprehensive and realistic framework. By incorporating the parallel mediating roles of information overload and information narrowing between multidimensional algorithmic characteristics (i.e., accuracy, novelty, and transparency) and information fatigue, this study presents a more complete causal structure. The findings elucidate how different dimensions of algorithmic recommendations collectively function through cognitive and informational burdens, thereby resolving the theoretical fragmentation regarding how algorithmic features translate into user fatigue in digital platforms.

Second, this research exhibits methodological superiority by overcoming the fundamental limitations of previous information systems research, which almost exclusively relies on linear, sufficiency-based logic (e.g., traditional SEM or regression). By integrating PLS-SEM and fsQCA, this study achieves a comprehensive understanding of the data, offering a deeper exploration of both linear net-effects and non-linear relationships. This hybrid logic validates that algorithmic dimensions (accuracy, novelty, transparency) and informational mediators are not only influential linear drivers but also interact in complex, asymmetric configurational recipes to trigger high information fatigue. This perspective captures causal complexity and is largely missing in the current recommender systems literature.

Third, this study enhances practical utility by applying combined importance-performance map analysis (cIPMA) to identify the critical performance thresholds and key bottlenecks required to mitigate information fatigue. Unlike prior studies that offer generic recommendations without priority, the application of cIPMA offers a robust tool that enables better prioritization of management actions to improve the key target construct. It provides a clear, evidence-based prioritization framework by distinguishing between essential algorithmic factors and underperforming ones. This enables platform designers and managers to more effectively allocate optimization resources to the specific algorithmic attributes (e.g., improving novelty or transparency) that have the strongest overall impact on alleviating information overload and fatigue, thereby addressing the shortcoming of previous research that considered importance but ignored performance constraints.

2. Literature Review and Research Hypotheses

2.1Cognitive Evaluation Theory

This study is based on Cognitive Evaluation Theory, which was first proposed by psychologist Lazarus (1993) as an emotion generation theory. It emphasizes the central role of an individual's subjective cognitive appraisal of external stimuli in the generation of emotional responses. Therefore, the cognitive appraisal process is an information processing procedure that serves as a causal determinant in emotional generation (Skavronskaya et al., 2021).

As a theoretical foundation and research framework in multiple fields, Cognitive Evaluation Theory can explain the process of cognitive formation and has been widely applied in areas such as psychology (Song et al., 2023) and business (Ouyang et al., 2017). This study posits that Cognitive Evaluation Theory can effectively explain the formation of user information fatigue. Firstly, the characteristics of algorithmic recommendations, as external situational stimulus variables, are subjectively perceived by users during their interaction with social media, particularly in aspects such as the repetitiveness, relevance, and redundancy of the recommended information. This perceptual process activates the user's cognitive appraisal system, primarily manifested through mediating variables such as information overload and the narrowing of accepted information. Ultimately, this series of processing steps leads to the user's information fatigue state, which is reflected in negative cognitive and emotional experiences, such as psychological exhaustion and avoidance of use.

In summary, Cognitive Evaluation Theory provides a solid theoretical foundation for this study. It emphasizes that external environmental features do not directly determine user behavior but instead trigger emotional responses through their activation and processing of users' subjective cognition. This theory not only helps reveal the intrinsic relationship between social media recommendation mechanisms and users' negative emotions but also provides a theoretical basis for platform optimization of recommendation strategies and the alleviation of users' negative emotions.

2.2Characteristics of Algorithmic Recommendations and Information Overload

Algorithmic recommendation refers to the process of analyzing user data such as interests, behaviors, and preferences through algorithms, and subsequently providing personalized content recommendations to users (Lu et al., 2015). From the perspective of communication studies, an important research direction of algorithmic recommendations is their impact on users' information behavior (Santos et al., 2021). Studies generally suggest that algorithmic recommendations have changed the way people engage with information, leading users to gradually rely on algorithmic pathways and lose the motivation for actively exploring information (Balaji et al., 2021). According to Li (2024), the perceived characteristics of algorithmic recommendations can be divided into accuracy, novelty, and transparency. Accuracy ensures that the recommended content closely matches the user's interests (Isufi et al., 2021; Shin, 2020). Novelty maintains user satisfaction by introducing content that

the user has not previously encountered (Castells et al., 2022). Transparency helps address users' perceived privacy risks(Pu et al., 2022), thereby enhancing users' trust in the platform.

Information overload refers to the situation where users may receive more information than they are capable of processing on social media platforms (Karr-Wisniewski et al., 2010). Regarding the relationship between accuracy and information overload, scholars argue that excessive accuracy leads to users receiving too much of the content they like. Given the limited capacity for information processing, users may experience heightened pressure as they attempt to process the overwhelming amount of information (Qaisar et al., 2022). Other scholars have pointed out that frequent content recommendations aligned with users' interests may lead them into a dilemma of choice. Users need more cognitive resources to prioritize and select what to process, thereby intensifying the pressure of information overload (Ma et al., 2021). Especially on social media platforms, algorithms push accurate content to users, achieving personalized recommendations with a 'one size fits one' approach. According to cognitive appraisal theory, the external information environment presented by the platform is a crucial precursor to users' emotional and behavioral responses. When algorithmic recommendations become excessively accurate, it increases users' information processing pressure and cognitive load, activating their stress appraisal of the information environment and resulting in the perception of information overload. Therefore, the following hypothesis is proposed:

H1a: The accuracy of algorithmic recommendations positively influences information overload.

The transparency of algorithmic recommendations refers to the platform's ability to explain the logic behind the recommendations, requiring the platform to provide users with adequate explanations (Li et al., 2024). Due to the complex and opaque internal workings of algorithmic recommendations, they are often referred to as the algorithmic black box(Mahmud et al., 2022; Pedreschi et al., 2019). Rai (2020) criticized the lack of explainability in algorithmic systems and called for transparency to be incorporated as a design principle and governance form. In recent years, the frequent occurrence of issues such as algorithmic bias and misuse has further amplified the call for greater algorithmic transparency (Ananny & Crawford, 2018). However, from the perspective of users' psychological perception, increased algorithmic transparency is not always a positive source of experience. When platforms provide users with more information about the recommendation mechanisms, data sources, and content generation rules, users need to process additional complex information about how the algorithm operates while browsing content, which increases their cognitive load. Therefore, this study proposes the following hypothesis:

H1b: The transparency of algorithmic recommendations positively influences information overload.

Repeatedly recommended content can lead users into choice fatigue and cognitive congestion, while content with high novelty, due to its distinctiveness and unpredictability, can capture attention and spark interest, thereby effectively alleviating information load (Kim et al., 2018; Chambers, 2024). Based on the incentive-sensitization theory, the novelty and diversity of information help maintain cognitive stimulation and interest among the audience (Kuem et al., 2021). Alleviating cognitive pressure. At the

same time, according to curiosity-driven theory, users possess an inherent curiosity and actively engage in exploratory behavior to seek out different information (Berlyne, 1960). Highly novel recommended content can satisfy this motivation, enhancing users' willingness to process information and the quality of their information experience. Therefore, content with high novelty, due to its distinctiveness and stimulus, can alleviate the burden of repetitive information to some extent, reducing users' sense of pressure from the volume of information. Based on the above, the following hypothesis is proposed:

H1c: The novelty of algorithmic recommendations negatively influences information overload

2.3Algorithmic Recommendation Features and Information Narrowing

Information narrowing refers to the process where personalized recommendation systems push content that excessively matches users' preferences, causing their interests to become increasingly focused on a specific domain, lacking diversity and novelty (Huang et al., 2020). Although this personalized push may enhance user engagement in the short term, in the long run, users may feel the monotony and repetitiveness of the information, losing interest in exploring other content. Information narrowing not only limits users' exposure to new information but may also lead to the creation of filter bubble effects and echo chamber effects (Nguyen et al., 2014). Some studies have pointed out that the pursuit of accuracy in algorithmic recommendations may negatively impact the user experience, especially for new users, causing them to fall into the 'similarity trap (Li et al., 2024). More importantly, high accuracy in recommendations may lead users to repeatedly receive similar content, reinforcing their inherent biases and preferences, which ultimately results in the formation of an information cocoon (Castells et al., 2022; Lin et al., 2023). Social media platforms often target short-term click-through rates, retaining users with content that has high recommendation accuracy. This behavior easily leads users into a preference echo where the more users tend toward a certain type of content, the more the system pushes that same type of content, resulting in the information cocoon effect. Therefore, the following hypothesis is proposed:

H2a: The accuracy of algorithmic recommendations positively influences information narrowing.

Transparency, as a trust bridge between the platform and users, helps enhance users' trust in the algorithmic recommendation system and their perception of fairness (Shin 2021). Users prefer 'transparent' algorithmic systems and have more confidence in them (Cabiddu et al., 2022). According to cognitive appraisal theory, an individual's judgment of external information contexts affects their subsequent psychological and behavioral responses. When platforms reveal the recommendation logic to users, the psychological implication of the algorithm knows what I want fosters trust in the algorithm, which in turn leads to the acceptance and reinforcement of a single type of information intake path. This cognitive compliance tendency weakens users' willingness to actively explore diverse information. Therefore, the following hypothesis is proposed:

H2b: The transparency of algorithmic recommendations positively influences information narrowing.

Information narrowing means that the recommendation system fails to meet users' diversified information needs (Ma et al., 2022). .It greatly reduces the perceived novelty of the recommendations, thereby diminishing the flow experience and making it more likely to cause the information cocoon effect (Zhao et al., 2023). Novelty is an important dimension of information quality (DeLone et al., 2003). Social media users are more active in selecting and sharing novel information (Cappella et al., 2015). Novel content breaks users' existing preference boundaries, guiding them to engage with a broader range of topics and perspectives. This helps expand their information boundaries and counteracts the trend of information uniformity. Therefore, the following hypothesis is proposed:

H2c: The novelty of algorithmic recommendations negatively influences information narrowing.

2.4Algorithmic Recommendation Features and Information Fatigue

Information fatigue is typically characterized by feelings of exhaustion, boredom, and resistance to information that arise after prolonged exposure to large volumes of information (Ravindran., 2014; Zhang et al., 2016; Teng et al., 2022). This phenomenon is widespread on social media platforms, where users often feel that they have wasted time or spent half an hour without gaining substantial information after scrolling through content. Such emotional reactions significantly affect long-term platform usage and users behavioral choices. Particularly with frequent use of social media, users may experience feelings like suddenly not wanting to continue halfway through, manifesting as indifference and alienation toward the platform's content. Users gradually feel that the constant stream of information fails to provide real value, leading to a perception of time wasted and, subsequently, a sense of resistance toward the social media platform.

On social media platforms, the system accurately recommends content of interest based on users' past behaviors, search history, and preferences (Bode et al., 2018). Although research has shown that information accuracy can reduce the cost of information search and the effort required for information processing, long-term and frequent exposure to highly accurate information can lead to cognitive and emotional fatigue (Khaleel et al., 2020). According to the incentive-sensitization theory, when users are continuously exposed to similar and repetitive stimuli, their perception of novelty and psychological responses to these stimuli gradually weaken, leading to psychological reactions such as decreased interest and emotional fatigue (Kuem et al., 2021). In other words, as the accuracy of recommendations increases and the content aligns more closely with user expectations, it is more likely to lead to content homogeneity and uniformity. While such content may align with user interests in the short term, its lack of novelty and diversity makes it difficult to sustain users' attention and emotional engagement. Therefore, the following hypothesis is proposed:

H3a: The accuracy of algorithmic recommendations positively influences information fatigue.

Although transparency may increase users' reliance on the volume and scope of information, from an emotional regulation perspective, the transparency of the recommendation system is typically seen as a

positive signal. It can alleviate users' anxiety about being manipulated and enhance platform interaction and trust (Shin, 2021; Huang et al., 2025). When users understand why they received a particular piece of content, even if the content itself is not novel or unexpected, they are less likely to experience emotional rejection or cognitive resistance (Shin, 2020). In other words, when users lack an understanding of the source and logic behind the platform's pushed content, they are more likely to experience feelings of helplessness and being manipulated, which increases psychological exhaustion and fatigue. Transparency in algorithmic recommendations, on the other hand, provides users with an understanding of the recommendation mechanism, enhancing their sense of understanding and control over the content. Based on this, the following hypothesis is proposed:

H3b: The transparency of algorithmic recommendations negatively influences information fatigue.

Although the accuracy of recommendations remains the primary criterion guiding recommendation system design, people have come to realize that relying solely on recommendation accuracy is not enough to ensure user satisfaction (Kunaver et al., 2017). Novelty, as an important dimension that stimulates users' exploratory interest and cognitive engagement, has become one of the key topics in recommendation system research. Repeatedly recommended content can lead users into choice fatigue and cognitive overload, whereas highly novel content, due to its differences and unpredictability, can capture attention, arouse interest, and effectively alleviate information overload (Kim et al., 2018; Chambers, 2024). Based on the incentive-sensitization theory, the novelty and diversity of information help maintain audience cognitive stimulation and interest (Kuem et al., 2021). At the same time, according to curiosity-driven theory, users have an inherent curiosity that drives exploratory behavior to learn different types of information (Berlyne, 1960). Highly novel recommended content can fulfill this motivation and alleviate user information fatigue. In other words, novel content stimulates users' desire for exploration and reduces fatigue from content repetition. Therefore, the following hypothesis is proposed.

H3c: The novelty of algorithmic recommendations negatively influences information fatigue.

2.5The Impact of Information Overload on Information Fatigue

Social media carries a vast amount of information. Although some of this information is beneficial to individuals, according to cognitive load theory, human cognitive capacity is limited. When the volume of information becomes excessive or tasks become overly complex, it can exceed cognitive processing capabilities, increase fatigue, and result in information overload (Lang, 2010; Sweller, 2011). Existing research has confirmed that information overload reduces users' interest in content, increases usage pressure, and ultimately triggers resistance to and fatigue toward information (Fu et al., 2024). Other studies have indicated that information overload on social media can lead to social media fatigue (Zhang et al., 2022).

Based on cognitive appraisal theory, when users frequently encounter highly similar, repetitive, and unoriginal information during their use of social media platforms, or when they do not understand the opaque content distribution mechanisms, it can easily trigger cognitive overload—an experience in which the volume of received information exceeds their cognitive processing capacity. Prolonged exposure to high levels of information load leads users to gradually lose interest and a sense of control over the information, resulting in psychological fatigue and emotional desensitization. Therefore, the following hypotheses are proposed:

H4a: Information overload positively influences information fatigue.

H4b: Information overload mediates the influences of accuracy on information fatigue.

H4c: Information overload mediates the influences of transparency on information fatigue.

H4d: Information overload mediates the influences of novelty on information fatigue.

2.6The Impact of Information Narrowing on Information Fatigue

On social media platforms, algorithms analyze users' past behaviors and preferences to continuously push content that users are "interested in" (Geschke et al., 2019). As a result, a "filter bubble" is formed, in which algorithms continuously narrow the scope of information available to users, excluding them from diverse content and information (Nguyen et al., 2014). Information narrowing not only limits users' information diversity and exploration space but also tends to weaken their cognitive stimulation and motivation to learn, trapping them in a "cognitive closed loop" that prevents exposure to new perspectives and experiences (Behera et al., 2020; Lee, 2023). Information narrowing not only limits users' information diversity and exploration space but also tends to weaken their cognitive stimulation and motivation to learn, trapping them in a "cognitive closed loop" that prevents exposure to new perspectives and experiences (Behera et al., 2020; Lee, 2023). In summary, the following hypotheses are proposed:

H5a: Information narrowing has a positive influences on information fatigue.

H5b: Information narrowing mediates the influences of accuracy on information fatigue.

H5c: Information narrowing mediates the influences of transparency on information fatigue.

H5d: Information narrowing mediates the influences of novelty on information fatigue.

2.7Complexity theory and research proposition

While prior studies on information fatigue have predominantly relied on linear and additive (net-effect) logic, such a paradigm may oversimplify the causal complexity and interactive nature between

multidimensional algorithmic features (e.g., accuracy, novelty, and transparency) and users' information perceptions (e.g., overload and narrowing) in digital platform contexts.

Drawing on complexity theory, this study adopts a configurational perspective to more comprehensively examine how multidimensional algorithmic recommendation features (accuracy, novelty, and transparency) and information cognitive appraisals (information overload and information narrowing) jointly contribute to information fatigue. Complexity theory has been increasingly applied across disciplines such as psychology and marketing to explain nonlinear, multifaceted, and interdependent phenomena (Woodside et al., 2015). This theoretical perspective supports the application of fuzzy-set Qualitative Comparative Analysis (fsQCA), which captures causal asymmetry and interdependence among conditions and has been shown to effectively explain complex user behavior(Zhang et al.,2026).

Complexity theory posits that social phenomena are characterized by causal complexity, in which outcomes emerge from the interaction of multiple interdependent conditions rather than from isolated, additive effects of individual variables (Pappas and Woodside, 2021). In the complex system of algorithmic recommendations on digital platforms, users' information fatigue is often the result of the simultaneous processing of multidimensional algorithmic features and cognitive cues such as information overload and narrowing. Therefore, relying solely on linear explanations, while necessary, is insufficient. Traditional symmetric research methods, such as regression analysis and partial least squares structural equation modeling (PLS-SEM), typically fail to uncover such non-linear and context-dependent causal mechanisms.

A central principle of complexity theory is equifinality, which suggests that the same outcome can be achieved through multiple distinct combinations of antecedent conditions (Eastman et al., 2024). In the context of algorithmic recommendations on digital platforms, users may develop high levels of information fatigue through different cognitive and experiential pathways. For example, some users might be more susceptible to the combination of high algorithmic accuracy and severe information narrowing; whereas others might experience the same level of fatigue when a lack of algorithmic transparency is coupled with high information overload. These alternative pathways indicate that no single algorithmic feature or cognitive appraisal universally determines users' negative responses across all contexts; rather, different configurational combinations of multidimensional algorithmic features and information stressors can be equally effective in triggering information fatigue.

Another important principle of complexity theory is causal asymmetry, meaning that the conditions leading to high levels of an outcome are not simply the inverse of those leading to low levels of the same outcome (Pappas and Woodside, 2021). In the context of algorithmic recommendations on digital platforms, the absence of certain algorithmic features (e.g., transparency) might be a critical condition for triggering high information fatigue in some configurations, but its presence does not necessarily produce the exact opposite effect across all situations. This asymmetric logic challenges the fundamental assumption embedded in traditional symmetric research methods, which assumes that

positive and negative outcomes are driven by the same variables operating in opposite directions. Based on these assumptions, this study proposed:

Proposition

In the context of algorithmic recommendations on digital platforms, there is no single "best configuration" of algorithmic accuracy, novelty, transparency, information overload, and information narrowing that uniquely leads to high levels of information fatigue. rather, multiple configurations of different causal conditions can jointly yield this outcome.

The research model is shown in Fig. 1.

3. Methodology

3.1. Data collection and respondent profile

The data for this study were collected through the professional survey platform “Wenjuanxing”. Based on a class of students from a university in northern China, a snowball sampling approach was employed. The questionnaire was distributed via social media, and data authenticity was ensured through IP address verification and consistency checks. The data collection process was designed to ensure the reliability and validity of the research findings. This study confirmed that informed consent was obtained from all participants and/or their legal guardians. Participants were informed that the questionnaire survey was conducted solely for academic research purposes and would not be used for any other purposes. They were also informed that they could discontinue participation at any time if they experienced any discomfort during the survey process.Confirm that all research was performed in accordance with relevant guidelines/regulations, This study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of Tianjin University of Sport (Approval No. TJUS-2025-095).

At the beginning of the survey, participants were first asked a screening question: “Have you used social media platforms based on algorithmic recommendations?” Only respondents who answered “yes” were allowed to proceed. Finally, 463 valid responses were obtained from individuals aged 18 years and above residing in China. The sample consisted of 61.3% male and 38.7% female respondents. In terms of age distribution, 38.9% of participants were concentrated in the 25–34 age group, and 39.1% reported spending 2–4 hours per day on social media. The demographic characteristics of the sample are broadly consistent with the profile of core active users on social media platforms, indicating that the sample demonstrates satisfactory representativeness.

Table 1
Demographic descriptive

Statistical items	Specific Content	Statistical Value	Percentage
gender	male	284	61.3%
	female	179	38.7%
age	under 18	38	8.2%
	18–24	94	20.3%
	25–34	180	38.9%
	35–44	101	21.8%
	Over45	50	10.8%
education	Under high school	121	26.1%
	Junior college	140	30.2%
	college	140	30.2%
	Master/Phd	62	13.4%
daily social media use	Less 30 minutes	25	5.4%
	30 minutes–1 hour	49	10.6%
	1–2 hour	117	25.3%
	2–4 hour	181	39.1%
	More than 4 hours	91	19.7%
Years of social media use	Less 1year	81	17.5%
	1–3 year	149	32.2%
	3–6 year	133	28.7%
	More than 6 year	100	21.6%

3.2 Measures

All variables in this study were adapted from previous research. The characteristics of algorithmic recommendation (accuracy, novelty, and transparency) were adapted from Li et al. (2024). Information overload was adapted from Yang et al. (2025) and Lv et al. (2024). It adapted three items from Zhang et al. (2024) and Khoi (2024) to measure information narrowing. The information fatigue scale was adapted from Zhong et al. (2024) and Qiao et al. (2024) and measured using four items. All items were assessed using a seven-point Likert scale (ranging from 1 = “strongly disagree” to 7 = “strongly agree”).

4.Date analysis

4.1Reliability and Validity Analysis

Reliability analysis refers to the degree to which the same results are produced when the same method is used to repeatedly measure the same object, indicating the stability, consistency, and dependability of the measurement.

Validity refers to the extent to which a measurement tool or method accurately reflects the target being measured. The specific results of the reliability and validity tests are shown in Table 2. The factor loadings range from 0.785 to 0.904, and all measurement items meet the standard. The Cronbach's α values for all variables exceed 0.8, and the CR values are all above the acceptable threshold of 0.7, indicating that the scales meet the reliability criteria (Hair et al., 2019). The AVE values for all variables are greater than 0.5, indicating that the convergent validity is also satisfactory (Fornell & Larcker, 1981).

Table 2
Reliability and Convergent Validity Analysis

Latent variable	Items	Factor loadings	Cronbach's α	CR	AVE
accuracy(AC)	AC1	0.875	0.831	0.832	0.747
	AC2	0.856			
	AC3	0.861			
transparency(TR)	TR1	0.859	0.851	0.869	0.689
	TR2	0.835			
	TR3	0.785			
	TR4	0.841			
novelty(NO)	NO1	0.874	0.829	0.841	0.746
	NO2	0.813			
	NO3	0.901			
information Overload(IO)	IO1	0.820	0.870	0.870	0.720
	IO2	0.854			
	IO3	0.844			
	IO4	0.875			
information narrowing(IN)	IN1	0.859	0.850	0.853	0.770
	IN2	0.869			
	IN3	0.904			
information Fatigue(IF)	IF1	0.822	0.853	0.855	0.693
	IF2	0.829			
	IF3	0.852			
	IF4	0.828			

The results of the discriminant validity test are shown in Table 3. The square root of the AVE values (numbers on the diagonal) all exceeded the Pearson correlation coefficients between the variables, indicating that the scale has good discriminant validity (Fornell & Larcker, 1981). Based on the calculation results in Table 3, it can be observed that the square root of the AVE for all latent variables (values on the diagonal) is greater than their correlation coefficients with other variables, indicating substantial differences among the measurement items and good discriminant validity for each latent variable. Under the unrotated condition, a total of six factors had eigenvalues greater than 1, while the

total variance explained by the first factor did not exceed the standard threshold of 40% (Podsakoff et al., 2003). Therefore, the data were not affected by common method bias.

Table 3
Discriminant Validity Analysis

Latent variable	AC	TR	NO	IO	IN	IF
AC	0.864					
TR	0.165	0.830				
NO	-0.256	-0.151	0.863			
IO	0.430	0.317	-0.446	0.848		
IN	0.291	0.129	-0.374	0.482	0.877	
IF	0.239	0.112	-0.429	0.535	0.530	0.833

Note:Accuracy TR=Transparency NO=Novelty IO=Information Overload IN=Information Narrowing IF=Information Fatigue

4.2Structural Equation Model Testing Results

This study used SmartPLS 4.1 software to construct the model and paths, and employed Bootstrapping with 5,000 resamples to test the significance of the path coefficients. The data analysis results indicate that the accuracy of algorithmic recommendations ($\beta = 0.309$, $p < 0.001$) and transparency ($\beta = 0.216$, $p < 0.005$) both have a positive effect on information overload, while novelty ($\beta = -0.335$, $p < 0.001$) has a negative effect on information overload. Accuracy ($\beta = 0.203$, $p < 0.001$) positively affects information narrowing, novelty ($\beta = -0.315$, $p < 0.001$) negatively affects information narrowing, and transparency ($p = 0.393 > 0.05$) has no effect on information narrowing. Moreover, accuracy ($p = 0.521 > 0.05$) and transparency ($p = 0.978 > 0.05$) have no significant effect on information fatigue, while novelty ($\beta = -0.177$, $p < 0.001$) has a significant negative effect on information fatigue. Both information overload ($\beta = 0.335$, $p < 0.001$) and information narrowing ($\beta = 0.320$, $p < 0.001$) have significant positive effects on information fatigue.

In addition, the study found that accuracy (95% Boot CI = [0.054, 0.155]) and transparency (95% Boot CI = [0.027, 0.124]) both trigger information fatigue through information overload, indicating a positive mediating effect. Information overload plays a negative mediating role in the relationship between novelty and information fatigue (95% Boot CI = [-0.170, -0.050]). Furthermore, accuracy (95% Boot CI = [0.031, 0.106]) triggers information fatigue through information narrowing, showing a positive mediating effect. Information narrowing does not have a significant mediating effect in the relationship between transparency and information fatigue (95% Boot CI = [-0.020, 0.051]), while it plays a negative mediating role in the relationship between novelty and information fatigue (95% Boot CI = [-0.152, -0.059]). The results are presented in Table 4.

Table 4
Hypothesis Testing Results

Direct Effects	**β**	**T**	**P**	**Conclusion**	
H1a:AC->IO	0.309	4.131	0.000***	Supported	
H1b:TR->IO	0.216	3.448	0.001***	Supported	
H1c:NO->IO	-0.335	6.316	0.000***	Supported	
H2a:AC->IN	0.203	3.758	0.000***	Supported	
H2b:TR->IN	0.047	0.854	0.393	not	
H2c:NO->IN	-0.315	6.295	0.000***	Supported	
H3a:AC->IF	-0.034	0.643	0.521	Not	
H3b:TR->IF	-0.057	0.058	0.978	Not	
H3c:NO->IF	-0.177	3.651	0.000***	Supported	
H4a:IO->IF	0.335	5.304	0.000***	Supported	
H5a:IN->IF	0.320	6.794	0.000***	Supported	
Indirect effect	**Effect value**	**T**	**95%CI**	**P**	**Conclusion**
H4b: AC->IO->IF	0.103	4.063	[0.054,0.155]	0.000***	Supported
H4c:TR->IO->IF	0.072	2.915	[0.027,0.124]	0.004***	Supported
H4d:NO->IO->IF	-0.012	3.707	[-0.170,-0.050]	0.000***	Supported
H5b:AC->IN->IF	0.065	3.377	[0.031,0.106]	0.001***	Supported
H5c:TR->IN->IF	0.015	0.843	[-0.020.0.051]	0.399	not
H5d:NO->IN->IF	-0.101	4.211	[-0.152,-0.059]	0.000***	Supported

Note:Accuracy TR=Transparency NO=Novelty IO=Information Overload IN=Information Narrowing IF=Information Fatigue. *P<0.05, **P<0.01

4.3 Combined importance-performance map analysis(cIPMA)

cIPMA (combined Importance-Performance Map Analysis) extends the application of importance-performance map analysis (IPMA) in PLS-SEM by introducing the findings of NCA (Hauff et al., 2024). While PLS-SEM relies on sufficiency-based logic to pinpoint 'should-have' attributes that drive performance, the incorporation of NCA's necessity logic allows for a dual-perspective assessment. This hybrid approach enables a more nuanced prioritization of managerial actions by identifying factors that are both performance-enhancing and essential for the target outcome.

First, we applied Importance-Performance Map Analysis (IPMA) to identify latent constructs that exhibit strong predictive relevance but demonstrate suboptimal performance in explaining key endogenous outcomes (Ringle and Sarstedt, 2016). This technique evaluates both the total effect and the average latent variable score. The findings indicate that information narrowing (0.32), information overload (0.335), and novelty (− 0.398) are the most important variables influencing information fatigue, with novelty (− 0.398) demonstrating a strong negative effect. In contrast, accuracy and transparency are the least important variables.

Following the running of IPMA, the rescaled latent variable scores are utilized in Necessity Condition Analysis (NCA) (Hauff et al., 2024) to uncover necessary conditions in the data (Dul, 2016b). According to Dul et al. (2023), the CE-FDH method yields an upper bound accuracy of 100%. A variable qualifies as a necessary condition when it demon strates at least a moderate effect size($d \geq 0.1$) and reaches statistical significance($p < 0.05$)(Dul et al.,2023).The NCA results show that information overload($d = 0.028, p > 0.05$), information narrowing($d = 0.013, p > 0.05$),novelty($d = 0.000, p > 0.05$) and transparency($d = 0.000, p > 0.05$)were not significant necessary conditions for information fatigue. Necessary conditions can be evaluated in detail through the bottleneck table, which presents the minimum levels of predictors required to achieve specific outcomes, thereby highlighting necessity constraints rather than merely reflecting average effects. The bottleneck table (Table 5) reveals that across the range from the lowest level to the 95th percentile of information fatigue, none of the antecedent variables (information narrowing, information overload, accuracy, novelty, and transparency) constitute bottlenecks. This indicates that no specific level of these variables is required to achieve the corresponding degree of information fatigue. Only when information fatigue reaches 100% (i.e., the maximum level) do bottlenecks emerge: information narrowing must reach at least 33.333, and information overload must reach at least 62.527. In contrast, accuracy, novelty, and transparency still show no required threshold levels.

Table 5
Bottleneck table-CE-FDH(Percentages)

0.00%	Information fatigue	Information narrowing	Information overload	Accuracy	Novelty	Transparenct
	11.978	**NN**	**NN**	**NN**	**NN**	**NN**
5.00%	16.379	NN	NN	NN	NN	NN
10.00%	20.78	NN	NN	NN	NN	NN
15.00%	25.181	NN	NN	NN	NN	NN
20.00%	29.582	NN	NN	NN	NN	NN
25.00%	33.983	NN	NN	NN	NN	NN
30.00%	38.384	NN	NN	NN	NN	NN
35.00%	42.786	NN	NN	NN	NN	NN
40.00%	47.187	NN	NN	NN	NN	NN
45.00%	51.588	NN	NN	NN	NN	NN
50.00%	55.989	NN	NN	NN	NN	NN
55.00%	60.39	NN	NN	NN	NN	NN
60.00%	64.791	NN	NN	NN	NN	NN
65.00%	69.192	NN	NN	NN	NN	NN
70.00%	73.593	NN	NN	NN	NN	NN
75.00%	77.994	NN	NN	NN	NN	NN
80.00%	82.396	NN	NN	NN	NN	NN
85.00%	86.797	NN	NN	NN	NN	NN
90.00%	91.198	NN	NN	NN	NN	NN
95.00%	95.599	NN	NN	NN	NN	NN
100.00%	100	33.333	62.527	NN	NN	NN

Table 6
Results of cIPMA

Predicting construct	Performance	Importance	Percentage cases that do not meet necessary conditiona	Effect size(p value)
Information overload	0.335	60.8	0.0	0.028(n.s.)
Information narrowing	0.32	55.24	0.0	0.013(n.s.)
Novelty	0.398	55.64	0.0	0.000(n.s.)
Accuracy	0.144	60.83	0.0	0.000(n.s.)
Transparenct	0.04	57.51	0.0	0.000(n.s.)

Note: a denotes based on a desired sustainable performance outcome level of 80%. The original total effects were − 0.398 and − 0.04; the absolute values are used here to represent the strength of the effects.

Following the guidelines outlined by Hauff et al.(2024), this study develops a combined importance-performance map(Fig. 2). The x-axis represents the total effects of each predictor variable, reflecting their relative importance, while the y-axis indicates the average scores of the latent constructs, which represent performance.(Zhang et al.,2026).Black dots signify variables that do not qualify as necessary conditions. Based on the results of the bottleneck table, when setting the target outcome level at a conventional 80% all antecedent variables display “NN” (Not Necessary). This indicates that none of these variables qualify as necessary conditions for achieving the target level. As illustrated in the figure, information overload is located in the upper-right quadrant (high importance and high performance). Accuracy is situated in the upper-left quadrant (low importance and high performance). Meanwhile, information narrowing and novelty are positioned in the lower-right quadrant (high importance and low performance), and transparency falls into the lower-left quadrant (low importance and low performance).

4.4 Fuzzy-set qualitative comparative analysis(fsQCA)

4.4.1 Data Calibration

Since fsQCA originates from the concept of set membership, calibration of the measures is the first step in fuzzy-set analysis. For all variables, the direct calibration method will be used to represent membership scores. This process requires specifying three qualitative anchors: full non-membership, full membership, and a crossover point. Referring to Ragin’s research, 0.95 is set as the “full membership point,” 0.5 as the “calibration crossover point,” and 0.05 as the “full non-membership point,” and the samples are calibrated accordingly (Ragin et al, 2008). Since cases with a membership score of 0.5 are not included in the truth table analysis, to avoid having too many cases located exactly at the 0.5

crossover point during calibration and thus being excluded—potentially affecting the analysis results—this study follows Fiss's approach by adding 0.001 to the calculation (Fiss et al., 2011).

4.4.2 Necessity Analysis

The necessity analysis of conditions is used to indicate the extent to which a single conditional variable explains the outcome variable. Necessity analysis should be conducted prior to configuration analysis(Schneider et al., 2010). By calculation, the consistency and coverage of each individual antecedent variable and its negation were obtained. The consistency values for all antecedent variables were less than 0.9, indicating that the explanatory power of a single variable for the outcome is relatively weak. Therefore, this study needs to combine multiple antecedent conditions for sufficiency analysis. The analysis results are shown in Table 5.

Table 7
Results of Necessity Analysis

Antecedent Condition	**Non-high Information Fatigue**	
	Consistency	**Coverage**
AC	0.635	0.680
~AC	0.755	0.823
TR	0.611	0.724
~TR	0.765	0.759
NO	0.717	0.795
~NO	0.610	0.642
IN	0.556	0.607
~IN	0.754	0.806
IO	0.574	0.659
~IO	0.793	0.809

4.3 Configuration Analysis

In conducting the fsQCA, and in line with previous research, this study sets the consistency threshold at 0.8, the PRI consistency threshold at 0.6, and the case frequency threshold at 5. The analysis results are shown in Table 6.To determine the extent to which a configuration serves as a sufficient condition for the outcome variable and its explanatory power, fsQCA uses two indicators: consistency and coverage.

Generally, configurations with a consistency ≥ 0.8 and coverage ≥ 0.5 are considered acceptable. As shown in Table 6, in this study, there are six configurations leading to non-high information fatigue, with consistencies of 0.886, 0.904, 0.929, 0.896, 0.892, and 0.963, respectively. The overall consistency

reaches 0.825 (> 0.8), and the overall coverage reaches 0.817 (> 0.5). This indicates that these six combinational paths are sufficient conditions for non-high information fatigue when users engage with algorithm-recommended social media. The overall coverage of 0.817 (> 0.5) further shows that these six configurations together explain more than 80% of the cases. Core conditions are represented by a large black dot (●), while peripheral ones are marked with a smaller black dot (•). A cross signifies (⊗) indicates the absence of a core condition, (⊗) indicates the absence of a peripheral condition.while an empty cell suggests no distinct inclination toward the condition's presence or absence (Pappas and Woodside, 2021).Table 8 and Fig. 4 presents six fsQCA configuration solutions.

Configuration 1: The absence of information overload acts as the decisive core condition, supported by the peripheral presence of novelty. This indicates that for these users, the fundamental strategy to avoid algorithmic fatigue is to strictly prevent information overload. As long as the sheer volume of algorithmic recommendations is kept in check (the core driver), occasional novel content (the peripheral driver) serves as a supplementary stimulus to maintain engagement without causing cognitive exhaustion.

Configuration 2: The absence of transparency, novelty, and information narrowing collectively form the core conditions. This path represents a passive or disconnected user state. When the algorithmic platform fundamentally lacks structural transparency, fails to provide novel stimuli, and does not narrow down information to specific interests, users simply do not invest cognitive resources. This complete lack of deep algorithmic engagement decisively prevents the onset of information fatigue.

Configuration 3: The absence of accuracy, information narrowing and information overload serve as the core conditions. This configuration portrays users who experience low fatigue by decisively avoiding high-stakes or intensely focused content. By fundamentally not demanding high accuracy, bypassing algorithmically narrowed "filter bubbles," and staying away from overwhelming information volumes, their cognitive load remains at a baseline level, thereby preventing fatigue.

Configuration 4: The absence of accuracy, transparency and information overload are the core conditions. Similar to NH3, this path shows that users can maintain low fatigue when they are entirely unconcerned with the quality (accuracy) or the mechanics (transparency) of the algorithm, provided that they are decisively not bombarded with excessive content (absence of overload). This reflects a highly casual, low-involvement browsing behavior.

Configuration 5: The absence of information narrowing is the sole core condition, while the presence of accuracy and information overload act as peripheral conditions. This is a theoretically insightful path: it reveals that escaping the algorithmic "filter bubble" (the core absence of narrowing) is the primary, decisive driver for alleviating fatigue. Even if users are peripherally exposed to a high volume of information (overload) that is accurate, the very act of receiving diverse, non-narrowed content decisively prevents the claustrophobic cognitive exhaustion typically associated with highly curated algorithmic feeds.

Configuration 6: The absence of accuracy is the core condition, supplemented by the peripheral presence of transparency novelty and information narrowing. This configuration perfectly captures the "mindless scrolling" or entertainment mode on algorithmic platforms. The decisive factor keeping fatigue low is that the consumed information requires zero rigorous cognitive verification (the core absence of accuracy). The algorithm supports this effortless consumption by providing transparent, novel, and highly personalized (narrowed) content on the periphery, keeping users entertained without mental strain.

Table 8
Configurations for Low Information Fatigue

Antecedent Condition	**NH1**	**NH2**	**NH3**	**NH4**	**NH5**	**NH6**
AC			⊗	⊗	●	⊗
TR		⊗		⊗		●
NO	●	⊗				●
IN		⊗	⊗		⊗	●
IO	⊗		⊗	⊗	●	
Raw Coverage	0.629198	0.431031	0.581505	0.62293	0.409237	0.316807
Unique Coverage	0.045313	0.0116991	0.0887132	0.0294379	0.0342857	0.0584757
Consistency	0.886774	0.904038	0.929317	0.896668	0.892055	0.963131
Overall Coverage	0.817392					
Overall Consistency	0.825032					

Note:Accuracy TR=Transparency NO=Novelty IO=Information Overload IN=Information Narrowing IF=Information Fatigue.

Figure 3. Six types of configurations for Low Information Fatigue. Notes: dark blue circles presence of peripheral conditions, and light blue represent absence of core conditions.

5. Discussion

5.1 Research Conclusions

This study employed a mixed research method combining PLS-SEM and fsQCA, and the analysis yielded the following conclusions:

Information overload and information narrowing both have significant positive effects on information fatigue. Accuracy has a significant positive effect on information overload and information narrowing, but no direct effect on information fatigue; however, it can influence information fatigue indirectly through the mediating effects of information overload and information narrowing. Transparency has a significant positive effect on information overload, no effect on information narrowing or information fatigue directly, but exerts a significant positive effect on information fatigue through the mediating roles of information overload and information narrowing. Novelty has significant negative effects on information overload, information narrowing, and information fatigue. Information overload and information narrowing play significant negative mediating roles in the relationship between novelty and information fatigue.

Based on the fsQCA configurational analysis, six distinct paths were identified. This indicates that no single factor alone can account for the occurrence of low information fatigue; rather, it is the configuration of multiple conditions that produces the influencing factors leading to low information fatigue.

Finally, the cIPMA results indicate that no single antecedent variable constitutes a strictly necessary condition (bottleneck) for achieving the target outcome. This finding is fundamentally consistent with the fsQCA results, further confirming that alleviating information fatigue does not rely on the absolute prerequisite of any single factor, but rather depends on the configuration of multiple conditions. However, from the perspective of sufficiency and performance, "information narrowing" and "novelty" are located in the high-importance but low-performance quadrant. Meanwhile, "information overload" is situated in the high-importance and high-performance quadrant, whereas "accuracy" and "transparency," due to their relatively low total effects, hold a lower priority in intervention strategies aimed at directly alleviating fatigue.

5.2 Discussion

Information overload and information narrowing, as two typical information load variables, both exert significant positive effects on users' information fatigue, consistent with the findings of Pang (2021), Ma et al. (2021), and Lv (2024). When algorithm-driven social media platforms push massive amounts of content to users, they must receive and process large volumes of information in a short time, leading to continuous depletion of cognitive resources. This high-intensity information intake tends to cause attention dispersion and psychological tension. Moreover, given that content on social media is often short and fragmented, users can be exposed to a large amount of information in a brief period, making information fatigue more likely. Compared with the "quantitative" pressure of information overload, information narrowing manifests as "qualitative" uniformity and repetition. Long-term exposure to highly personalized and repetitive content compresses the perceived information space, causing users to gradually lose their curiosity and sense of discovery. This finding echoes the concepts of the filter bubble and echo chamber effects.

In addition, this study found that the accuracy of recommendation algorithms did not have a direct and significant impact on users' information fatigue, but it indirectly influenced fatigue through the two mediating variables—information overload and information narrowing. Although high recommendation accuracy can improve the match between content and user interests, prolonged exposure to highly consistent and repetitive information increases cognitive load and decision-making costs. At the same time, highly precise recommendations can trap users in a limited information loop, reducing their exposure to diverse content, thus restricting opportunities for cognitive expansion and reinforcing the filter bubble and echo chamber effects (Zhong et al., 2024; Yuan et al., 2022). According to cognitive appraisal theory, external technical features of recommendation algorithms, such as accuracy, do not directly trigger users' emotional or behavioral responses. Instead, they influence emotions through users' subjective cognitive appraisal, which transforms these features into perceived psychological load and stress. In other words, accuracy creates a cognitively dense and highly consistent environment, and it is the resulting sense of pressure within this environment that serves as the true cause of fatigue.

In this study, the transparency of algorithmic recommendations had no significant direct impact on information fatigue but influenced it indirectly through the mediating effects of information overload and information narrowing. This finding is inconsistent with the conclusions of Qin (2024) and Liu (2021). One reason is that the research sample consisted of general social media users, a relatively broad group, who tend to focus more on the entertainment value of the content itself and are less sensitive to algorithm transparency or recommendation logic. Another reason is that in the current highly fragmented social media environment, the density and repetitiveness of the content itself are the primary causes of fatigue, while transparency tends to be overlooked by ordinary users and thus fails to directly affect information fatigue. However, transparency can indirectly exacerbate users' sense of information fatigue through information overload and narrowing.On the one hand, transparency means that platforms disclose their algorithmic logic to users, but this process often reinforces users' perception of being manipulated. On the other hand, transparent algorithms do not reduce the volume of information received, so information overload and narrowing still occur, leading to fatigue.

Novelty has a direct negative impact on information fatigue, whereas accuracy and transparency influence it only indirectly through mediating effects. This indicates that novelty can not only directly reduce users' fatigue but also alleviate their information-processing burden and broaden their exposure to diverse information, thereby lessening fatigue. Compared with mere accurate matching, enhancing novelty tends to stimulate users' cognitive curiosity and emotional engagement, which in turn increases enjoyment, reduces the cognitive load, and lowers psychological resistance (Geng et al., 2023; Hong, 2021). Novelty has a certain "de-homogenization" function, which helps break the information cocoon and reduces the repetitive psychological drain on users.

Based on the fsQCA results, information overload is a core absent condition in the NH1 path, while novelty is a core present condition, which together can lead to low information fatigue. This suggests that when users perceive the recommended content as highly novel and do not experience significant information overload, they are more likely to maintain a positive usage state and avoid falling into

information fatigue. Novelty as a core present condition indicates that in the content recommendation process, users show strong interest in features that are “different from before” and “constantly changing.” Highly novel content can stimulate users’ curiosity and exploratory motivation. Meanwhile, low information overload plays the role of a cognitive protection mechanism—no matter how novel the content is, if the system pushes excessive amounts of it, users may still suffer from cognitive overload, leading to decision fatigue and psychological stress.

In the NH2, NH3, and NH5 paths, information narrowing appears as a core absent condition. Specifically, transparency and novelty as peripheral absent conditions form NH2; accuracy and information overload as peripheral absent conditions form NH3; and accuracy and information overload as peripheral present conditions form NH5. The absence of information narrowing directly weakens the triggers of information fatigue, indicating that maintaining the breadth and diversity of information input is a key approach for platforms to alleviate user fatigue and prevent burnout. When designing recommendation systems, platforms can achieve a balance between algorithms and users by incorporating diverse informational dimensions and avoiding structurally homogeneous content.

The NH4 path leading to lower information fatigue is characterized by the core absence of accuracy, transparency, and information overload. This indicates that this configuration represents a “de-systematized” combination, in which users experience low levels of fatigue in scenarios with minimal algorithmic intervention and very low platform information pressure. The simultaneous absence of accuracy and transparency suggests that, during their use of social media platforms, these users are less affected by the negative consequences of precise recommendations and the ongoing “algorithmic black box” effect. Such users may be in weak recommendation scenarios, or the platform’s capacity to capture and exploit individual features for recommendation is relatively limited, thereby reducing both their reliance on algorithmic mechanisms and their associated psychological burden.

The NH6 path shows the core absence of accuracy, the core presence of novelty, and the peripheral presence of transparency and information narrowing. This configuration indicates that the key to achieving low information fatigue on social media platforms lies not in the high degree of match between recommended content and user interests, but in the intrinsic novelty of the recommended content. The absence of accuracy does not trigger fatigue; instead, it may effectively avoid the “information cocoon” problem caused by overly precise recommendations. Prolonged exposure to highly consistent information tends to intensify users’ psychological fatigue, whereas novelty can continuously stimulate exploratory motivation and delay the onset of content-related boredom. Notably, NH6 has the highest consistency, suggesting that this is the optimal configuration for users to experience low information fatigue.

Finally, this study employed a combined Importance-Performance Map Analysis (cIPMA) to provide strategic prioritization for managing these variables and improving the target construct. The Necessary Condition Analysis (NCA) component revealed that none of the antecedent variables constitute strictly necessary conditions, or bottlenecks, for achieving the target outcome. This finding is fundamentally

consistent with the fsQCA results, further confirming that alleviating information fatigue does not rely on the absolute prerequisite of any single factor, but rather depends on the configuration of multiple conditions. However, from the perspective of sufficiency and performance, the IPMA map highlights that information narrowing and novelty are located in the high-importance but low-performance quadrant, indicating that priority of action should be given to these predictors. This identifies them as the highest priority areas for algorithmic optimization, as intervening in these two factors will yield the most significant reduction in user fatigue. Meanwhile, information overload is situated in the high-importance and high-performance quadrant, signifying it as a critical ongoing risk that requires continuous platform monitoring. In contrast, accuracy and transparency, due to their relatively low total effects, hold a lower priority in intervention strategies aimed at directly alleviating fatigue.

5.3 Methodological implications

The present investigation adopted an integrative methodological framework that combined PLS-SEM, cIPMA, and fsQCA to provide a robust and comprehensive understanding of users' information fatigue on algorithm-driven social media platforms. PLS-SEM established the foundational relationships among theoretical constructs, validating the hypothesized model and testing the proposed linear causal paths, including the mediating roles of information load and information narrowing variables. Moreover, NCA was applied to examine whether there are indispensable conditions that cannot be substituted if low levels of information fatigue are to be achieved, addressing necessity aspects often overlooked in traditional symmetric techniques. Next, cIPMA, as an extension of PLS-SEM, enabled the assessment of both the relative importance and performance of predictor constructs, thereby identifying key algorithmic optimization priorities—such as mitigating information narrowing and enhancing novelty—for alleviating user fatigue. Finally, fsQCA was employed to uncover equifinal pathways and configurational patterns of antecedents, thereby capturing causal asymmetry in users' information processing behaviors.

While each method has distinct individual advantages, their synergistic application offers unprecedented analytical depth and more nuanced interpretations of how algorithmic features shape users' psychological states. A single linear methodology could overlook the complexity of fatigue formation, which involves both linear and non-linear as well as sufficient and necessary relationships. Low information fatigue in algorithmic environments is not typically driven by a single factor; rather, it is shaped by a constellation of interrelated conditions, such as the interplay between recommendation accuracy, novelty, and information volume. Therefore, adopting this multi-method framework enhances methodological rigor and aligns with the inherent complexity of users' cognitive appraisals and psychological responses in modern digital platforms.

5.4 Practical Implications

This study offers several contributions for practical application: First, providing Guidance for Algorithm Optimization in Relevant Enterprises. The findings reveal that excessively accurate recommendations may lead to repetitive narrowing effects and user fatigue, whereas content characterized by novelty and

diversity can significantly ease users' cognitive load. Therefore, it is crucial to balance the tension between "relevance" and "diversity" by introducing unexpected content, out-of-interest recommendations, and trending social topics to stimulate users' curiosity, exploratory motivation, and positive experiences. Second, Addressing the Psychological Burden of High Accuracy and High Transparency. Platforms should remain aware of the mental strain that high-precision and highly transparent algorithms may impose. A gentler and more controllable algorithm–user interaction framework is recommended. While improving accuracy and openness, platforms should also provide users with more flexible control options—such as customizable parameters, manual refreshing of interest profiles, and enabling "exploration mode"—to reduce feelings of passivity and manipulation. Third, Enhancing Users' Awareness of Information Management. Users should actively regulate their pace of information intake, as personal information management plays a key role in alleviating information fatigue. In the face of high-intensity and high-frequency content pushes, users are advised to set personal limits on information reception, such as restricting push frequency, periodically "decluttering" information feeds, and taking intentional breaks from content consumption.

6. Limitations and Future Directions

This study has several limitations. First, the three algorithmic recommendation features examined in this research cannot fully capture the complete connotation of algorithmic recommendations; additional features could be incorporated in future studies. Second, users' negative reactions to algorithmic recommendations may take various forms, including resistance, perceptions of unfairness, and avoidance. However, this study focuses solely on information fatigue as the outcome variable and has not yet addressed other types of psychological and behavioral responses.

This study also offers prospects for future research. First, future studies could further differentiate among social media platforms. While this research takes social media platforms such as Douyin, Xiaohongshu, TikTok, and Kuaishou as representative cases, each platform has unique characteristics and subtle differences. Subsequent research could focus on a specific platform for in-depth analysis. Second, the scope of the survey could be expanded with more fine-grained data collection. For example, researchers could investigate and compare the behavioral habits of heavy, "addicted" users with those of users who spend less time on social media.

Abbreviations

AC	Accuracy
TR	Transparency
NO	Novelty
IO	Information Overload
IN	Information Narrowing
IF	Information Fatigue

Declarations

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All study procedures involving human participants followed the Helsinki Declaration. Prior to the commencement of the study, ethical approval was obtained from the Ethics Committee of Tianjin University of Sport (Approval No.: TJUS-2025-095). Informed consent was obtained from all study participants and their legal guardians.

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Figures

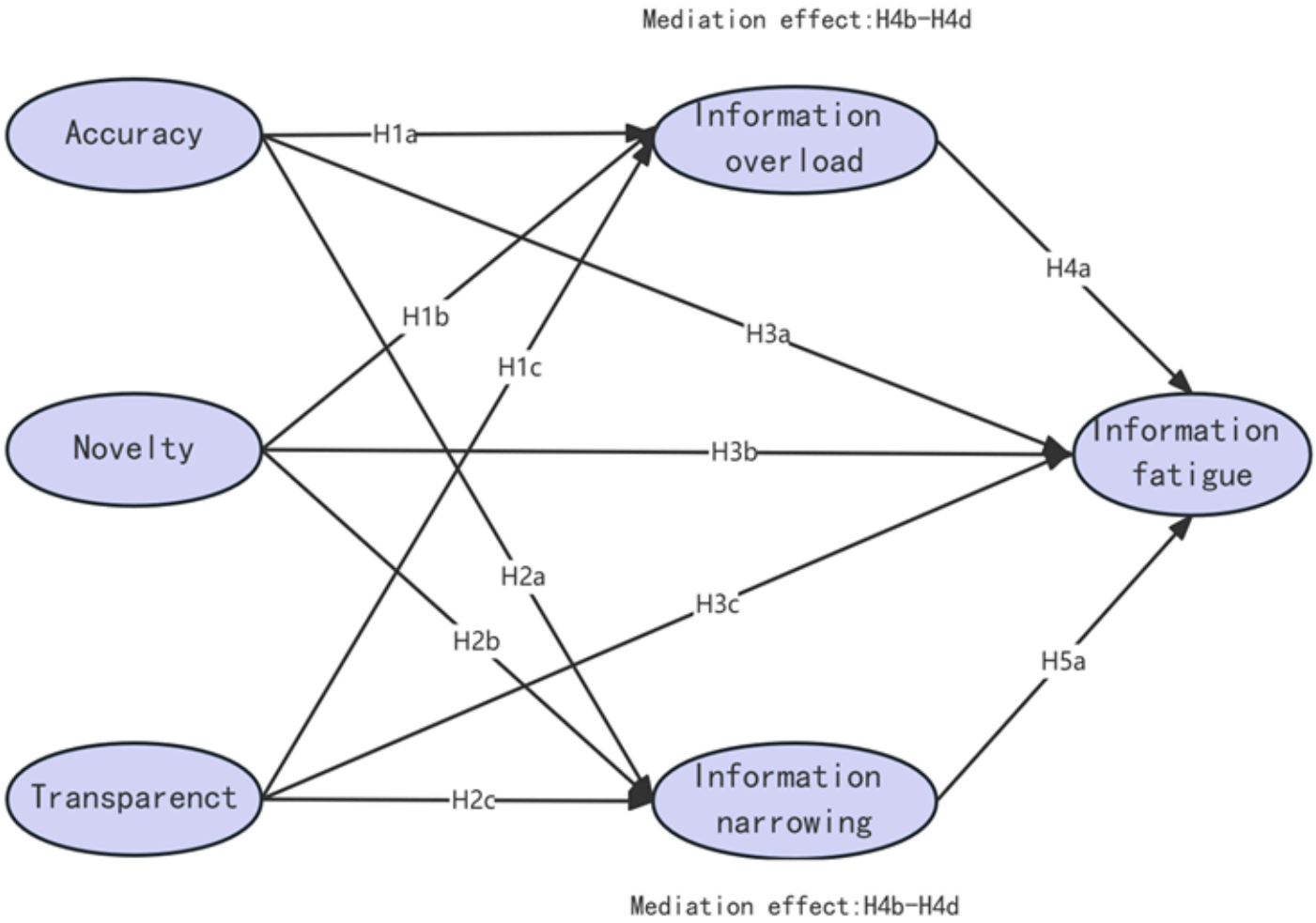


Figure 1

Research Model of the Effects of Algorithmic Recommendation Features on Information Fatigue

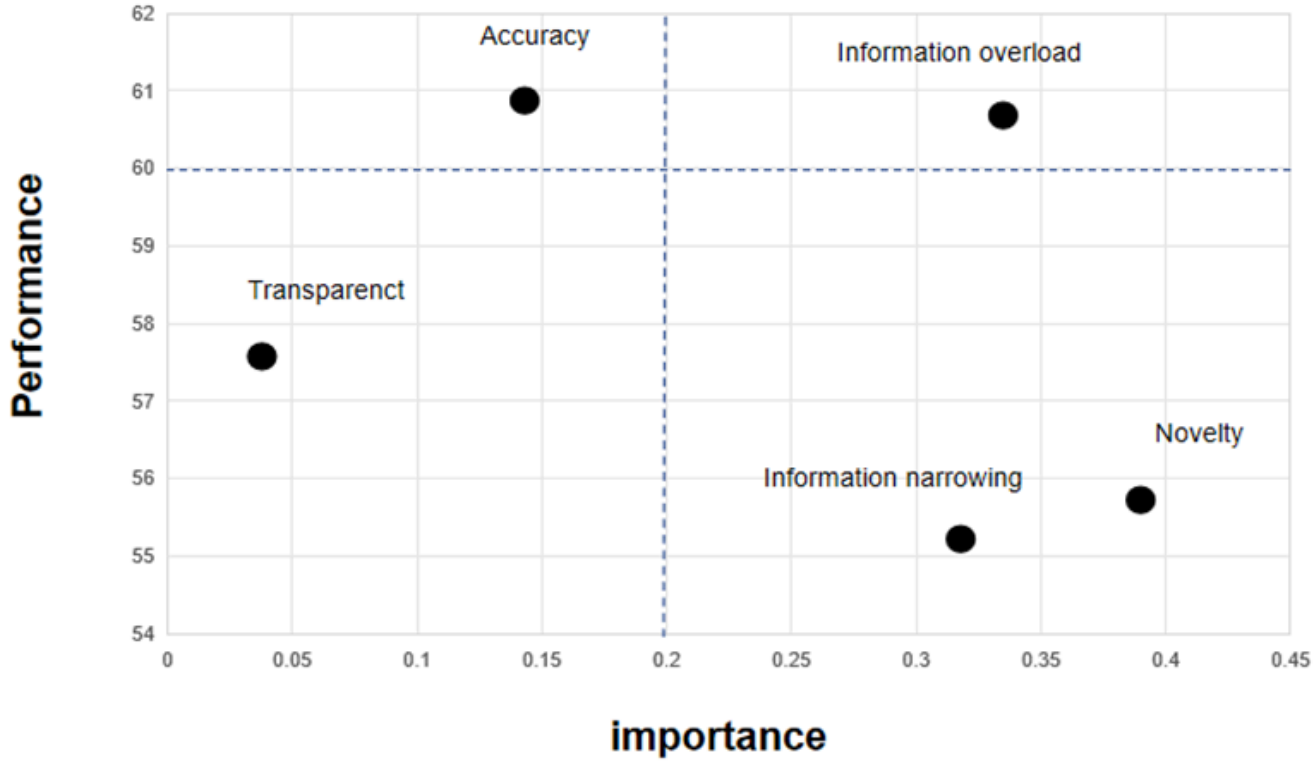


Figure 2

Combined importance-performance map of Information fatigue

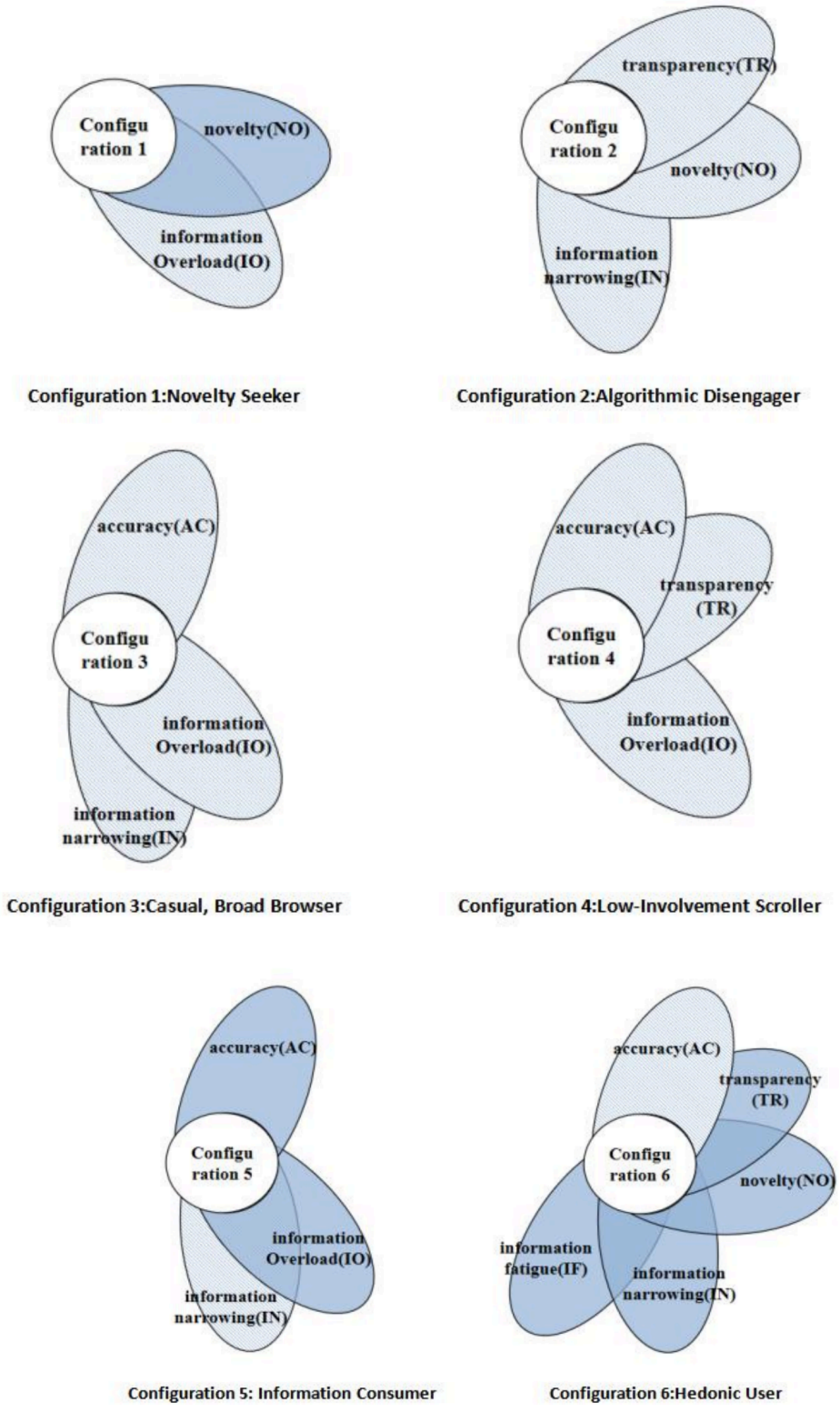


Figure 3

Six types of configurations for Low Information Fatigue. Notes: dark blue circles presence of peripheral conditions, and light blue represent absence of core conditions.

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- date.xlsx