



Article

“Cannot Stop, Yet Resent It”: How Short-Form Video Recommendation Algorithms Shape Users’ Continuance Intention

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Abstract

Short-form video platforms have become deeply embedded in everyday digital life, where algorithmic recommendation enhances user experience but also raises concerns about invasiveness and manipulateness. Drawing on the Cognitive–Affective–Conative (CAC) framework, this study examines the relationships between users’ cognitive evaluations of recommendation algorithms and continuance intention through algorithm dependence and algorithm aversion, while also identifying configurational pathways associated with high continuance intention. Based on 547 valid responses from short-form video users in China, we measured personalization, diversity, invasiveness, manipulateness, algorithm dependence, algorithm aversion, and continuance intention. PLS-SEM was used to test direct and mediating effects, and fsQCA was employed to identify sufficient configurations associated with high continuance intention. The results show that personalization and diversity positively predict continuance intention and exert significant indirect effects through algorithm dependence, whereas manipulateness negatively predicts continuance intention; invasiveness and algorithm aversion show no significant direct effects. The fsQCA results identify three dependence-maintenance pathways—experience-reinforced dependence, risk-buffered dependence, and risk-tolerant dependence—with algorithm dependence serving as a core condition across all four sufficient configurations. Notably, algorithm dependence and algorithm aversion coexist in two risk-tolerant configurations associated with high continuance intention. By distinguishing algorithm dependence from algorithm aversion, this study refines the affective dimension of the CAC framework, clarifies their differentiated roles in continuance intention, and provides configurational insights for responsible recommendation-system governance.

Keywords: short-form video; recommendation algorithms; continuance intention; algorithm dependence; algorithm aversion



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1. Introduction

With the deep integration of mobile internet and intelligent technologies, short-form video has become a central medium for everyday information consumption and emotional expression, owing to its brevity, efficiency, and interactivity. The core technology of these platforms—recommendation algorithms—analyzes users’ browsing trajectories, interactive behaviors, and interest tags in real time to achieve a “content-finds-user” matching model. This mechanism not only relieves users of the burden of filtering information but also substantially improves platforms’ retention and engagement. Recent research on TikTok further shows that intelligent recommendation can enhance users’ satisfaction and engagement

by improving their content experience [1]. According to the China Online Audio-Visual Development Report (2025), by December 2024, the number of short-form video users in China had reached 1.04 billion, with an average daily usage of 156 min, ranking first among all internet applications [2]. The efficiency and adaptability of recommendation algorithms have reshaped users' information consumption habits and become a key driver of platforms' competitive advantage.

As algorithmic intelligence advances, users may also encounter new risks while enjoying personalized recommendations. On one hand, algorithmic systems rely on extensive behavioral and contextual data to infer users' preferences, interests, and consumption tendencies, which may trigger concerns about privacy intrusion and data security [3,4]. On the other hand, recommendation mechanisms may shape users' exposure to information through content ranking, repeated pushing, and personalized filtering, thereby raising concerns about manipulateness [5,6]. In this sense, recommendation algorithms are not merely technical tools for improving matching efficiency; they also influence how users perceive platform control, information choice, and algorithmic risk. These contradictory experiences suggest that short-form video use involves both algorithmic benefits and perceived algorithmic risks.

However, it remains insufficiently understood how these positive and negative perceptions jointly shape users' continuance intention. On the one hand, algorithmic recommendation may create positive perceptions by providing users with convenient, relevant, and diverse content. On the other hand, it may also generate negative perceptions when users feel that their privacy boundaries or freedom of choice are being challenged [7,8]. The coexistence of these positive and negative perceptions raises an important question: why may users continue engaging with algorithmically recommended content even when they perceive certain algorithmic risks? Rather than treating continuance intention as a purely positive response to algorithmic benefits, it is necessary to examine the tension between algorithm dependence and algorithm aversion. This tension is particularly important in short-form video platforms, where algorithmic recommendation has become deeply embedded in users' everyday content consumption.

Existing research on short-form video algorithms and user behavior has made progress but still leaves several issues unresolved. From a research perspective, most studies emphasize the positive impacts of algorithmic benefits on continuance intention [9,10], or examine risk factors in isolation, such as privacy concerns [11] or transparency issues [12]. However, relatively limited attention has been paid to how algorithmic benefits and perceived risks operate simultaneously within the same explanatory framework. In particular, existing studies have not fully clarified whether positive perceptions mainly sustain continuance through algorithm dependence, or whether negative perceptions reduce continuance through algorithm aversion. This is important because the roles of algorithm dependence and algorithm aversion in shaping continuance intention remain insufficiently understood, particularly when users perceive both benefits and risks in algorithmic recommendation.

The Cognitive–Affective–Conative (CAC) framework provides a suitable lens for this study [13]. Recommendation algorithms may first shape users' cognitive evaluations of platform functions and algorithmic risks. These evaluations can subsequently give rise to affective orientations toward algorithmic recommendation, which constitute an intermediate stage between cognition and conative intention. In technology-use research, the affective component of CAC has been represented not only by emotional experiences but also by evaluative psychological states such as attitudes and satisfaction [14]. In this study, algorithm dependence (AD) and algorithm aversion (AA) represent two such affective orientations. AD reflects users' positively valenced psychological reliance on recommendation algorithms, whereas AA captures a negatively valenced emotional and evaluative

orientation toward them. These affective orientations may subsequently shape users' conative response, namely continuance intention. Beyond these individual relationships, prior studies have largely relied on net-effect approaches, such as Partial Least Squares Structural Equation Modeling (PLS-SEM), to examine linear relationships among variables. Although such approaches are useful for identifying direct and mediating relationships, they are less able to capture how different cognitive and affective conditions combine to produce high continuance intention. Therefore, a configurational perspective is needed to complement the net-effect analysis and reveal whether different combinations of algorithm-related perceptions, algorithm dependence, and algorithm aversion can lead to the same behavioral outcome.

In sum, current research has not sufficiently explained how users' cognitive evaluations of algorithmic recommendation are linked to distinct affective orientations and subsequent continuance intention, nor has it fully revealed the configurational pathways through which high continuance intention emerges. To address this gap, this study applies the Cognitive–Affective–Conative (CAC) framework to develop a theoretical model and explores the following research questions:

RQ1: How do users' cognitive evaluations of algorithmic recommendation shape continuance intention through algorithm dependence and algorithm aversion?

RQ2: What configurations of algorithm-related perceptions, algorithm dependence, and algorithm aversion are sufficient for high continuance intention?

2. Literature Review and Research Hypotheses

2.1. Cognitive-Affective-Conative Framework

The CAC framework is a foundational model for explaining psychological processes and behavioral intentions, rooted in the integration of philosophy and psychology. Aristotle's tripartite division of the soul into reason, emotion, and desire provided the foundation for this triadic structure. In modern psychology, McDougall [15] introduced the concept of "conation" as an instinctive tendency toward goal pursuit, emphasizing it as the core of motivation and challenging cognition-dominant perspectives. Lewin's [16] field theory further highlighted the dynamic balance among cognition, affect, and conation within the "field" of individual–environment interaction. Recent studies extend this line of inquiry. For instance, Paul et al. [17] demonstrated how positive affect interacts with cognitive processing to shape behavioral tendencies, while Maggino [13] showed how cognitive evaluations of external information directly shape affective experiences, which in turn regulate conative drive.

Structurally, CAC divides psychological activity into three interrelated dimensions [18]: cognition (information processing and understanding), affect (subjective experiences and physiological responses), and conation (willpower and action tendencies bridging cognition, affect, and behavior). These dimensions dynamically interact: cognition influences affect and conation, affect feeds back into cognition and conation, and conative outcomes reshape both cognition and affect, forming a complete psychological–behavioral chain.

Applied to technology contexts, CAC posits that both cognition and affect jointly shape behavioral intentions [19]. Cognition involves rational perceptions of technology attributes [20], whereas the affective stage concerns users' affective orientations formed in response to those evaluations before a behavioral intention is formed. Although affect is often represented by emotions and feelings, technology studies using the CAC framework have also operationalized this stage through broader evaluative states, including attitude and satisfaction [14]. Thus, the boundary between cognition and affect in CAC is better understood in terms of psychological function rather than whether a construct contains only emotion: cognition concerns what users believe or perceive about a technology, whereas

the affective stage concerns the positively or negatively valenced orientations users develop toward it following those evaluations. Conation, in turn, concerns intended or enacted behavioral responses [21].

Following this distinction, algorithm dependence and algorithm aversion are conceptualized as two affective orientations toward recommendation algorithms. Algorithm dependence reflects a positively valenced reliance orientation, whereas algorithm aversion reflects a negatively valenced emotional and evaluative orientation. These orientations occupy the affective stage between users' cognitive evaluations of algorithmic recommendation and their subsequent continuance intention.

2.2. User Cognition of Algorithms and Continuance Intention

CAC emphasizes that cognition directly or indirectly shapes behavioral intention, a logic widely validated in technology adoption studies [14,22]. In short-form video platforms, users' cognition of algorithms—formed from technical attributes and usage experiences—is a core determinant of their continuance intention [23]. The present study focuses on cognitive appraisals arising directly from users' recurring interactions with algorithmically curated feeds. These appraisals concern two fundamental aspects of recommendation use: the content delivered by the algorithm and the process through which recommendation is performed. At the recommendation-output level, personalization refers to the perceived extent to which the algorithm identifies users' preferences and tailors content accordingly, thereby facilitating access to personally relevant content. Diversity refers to the perceived breadth and variation in recommended content across categories, themes, creators, and repeated usage occasions. Together, they capture complementary evaluations of the relevance and variety of recommendation outputs [23,24]. At the recommendation-process level, invasiveness specifically concerns perceived encroachment on users' informational privacy boundaries through the collection, knowledge, or use of personal information, whereas manipulativeness concerns perceived algorithmic influence over users' attention, viewing choices, and autonomy [23,25,26]. Together, these four constructs capture distinct but complementary cognitive appraisals of what recommendation algorithms deliver and how the recommendation process is experienced by users.

Continuance intention refers to users' willingness to continue engaging with algorithmically recommended content through the platform's recommendation function [23]. Appraisals of recommendation relevance and variety can enhance the perceived value of continued algorithm use, whereas concerns about data boundaries and autonomy can weaken it. In short-form video, these cognitive dimensions affect behavior via benefit or risk perceptions [27].

From the perspective of personalization, algorithms analyze users' browsing histories, likes, and interactions to deliver content closely aligned with their interests. This process substantially reduces the cost of information filtering and enables users to quickly obtain the information or emotional gratification they seek [28]. When users perceive a higher degree of personalization, they are more likely to believe that continuance use of algorithms will yield stable and sustained value, thereby reinforcing their continuance intention. For example, Zhang et al. [29] found that users' perceptions of content quality and matching significantly increased their tendency to continue viewing. Regarding diversity, algorithms provide a wide variety of content—such as educational knowledge, lifestyle documentation, and creative storytelling—which helps users break free from filter bubbles, satisfy their exploratory needs, and expand cognitive boundaries. Once users perceive the recommended content as sufficiently diverse to prevent fatigue and continuously deliver novelty, they are more likely to consider long-term algorithm use valuable, thus strengthening their behavioral intention [30]. Li and Tuzhilin [31] further demonstrated that users' novelty-seeking

preferences align with “serendipitous” recommendations to enhance engagement and acceptance, as diverse content sustains long-term interest and mitigates boredom caused by content homogeneity.

Based on the above discussion, the following hypotheses are proposed:

H1. *Personalization positively influences continuance intention.*

H2. *Diversity positively influences continuance intention.*

Cognitive perceptions of invasiveness are closely linked to users’ privacy concerns. When users realize that algorithms excessively collect sensitive information—such as location data, voice recordings, and social connections—without explicit notice or sufficient authorization, they develop a perception of privacy risk. This perception generates doubts about continuing to use the algorithm and, in turn, weakens their continuance intention [32]. In the short-form video context, Xie et al. [33] found that when users feel they are being tracked, they often adopt algorithm-resisting strategies, thereby suppressing continuance. From the perspective of manipulateness, platform interfaces and algorithmic strategies (e.g., infinite scrolling, autoplay, frequent reminders/push notifications) undermine users’ autonomy. When users feel that the system deliberately prolongs their usage time or restricts their choices, they experience a sense of control loss and resentment, which reduces continuance intention or triggers resistance behaviors (e.g., reducing interactions, shortening use time, or deliberately “feeding false data” to the algorithm). Prior studies confirm this pattern: manipulative interfaces significantly alter user behavior and evoke resistance intentions [34]; algorithmic monitoring/control diminishes autonomy and strengthens resistance compared with human monitoring [26]; in short-form video scenarios, users counter algorithms through avoidance (less use/abandonment) and obfuscation (deliberately feeding false data) [33]; frequent push notifications further intensify disturbance and fatigue, prompting users to disable features and reduce subsequent usage intention [35].

Based on the preceding literature review, we propose the following hypotheses:

H3. *Invasiveness negatively influences continuance intention.*

H4. *Manipulativeness negatively influences continuance intention.*

2.3. User Cognition of Algorithms and Affective Orientations

In the short-form video context, users’ cognition of algorithms often gives rise to specific affective orientations. Affective orientations refer to positively or negatively valenced psychological stances toward an object that emerge from users’ cognitive evaluations and experiences. Among these, algorithm dependence and algorithm aversion are two important affective orientations toward recommendation algorithms [36,37]. Algorithm dependence refers to users’ psychological reliance on recommendation algorithms for content discovery, information filtering, and entertainment gratification. It captures the extent to which users come to rely on algorithmic recommendation as a convenient and effective way to access desired content. This form of reliance centers on users’ subjective dependence on algorithm-supported content access and differs conceptually from behavioral automaticity, trust judgments, emotional attachment, and compulsive use [23,38–40]. In contrast, algorithm aversion refers to users’ negatively valenced orientation toward recommendation algorithms, manifested as distrust, resentment, discomfort, dissatisfaction, or concern toward algorithmic recommendations. It reflects unfavorable emotional and evaluative responses to algorithmic recommendation and is conceptually distinct from perceived risk, psychological reactance, and overt avoidance behavior [41].

Cognitive perceptions of personalization and diversity are important antecedents of dependence. When algorithms continuously adapt to user preferences and deliver highly relevant content, they reduce search costs and increase users' psychological inclination to accept and rely on them. For example, in news recommendation systems, users who perceive that algorithms consistently push relevant topics and articles tend to reduce active searching and place greater trust in algorithmic judgments [42]. Similarly, in short-form video platforms, when algorithms respond flexibly to shifting user interests and provide contextually relevant content, users are more likely to develop greater psychological reliance on algorithm-supported content discovery [23]. Perceptions of diversity also significantly affect users' positive affective orientation toward algorithmic recommendation. When algorithms cover a wide range of categories and introduce novel topics in a timely manner, they maintain users' exploratory excitement and psychological satisfaction, thereby deepening positive attitudes and reinforcing dependence [24].

Conversely, cognitive perceptions of invasiveness and manipulateness are more likely to trigger negative affective orientations. When algorithms are perceived to excessively access or exploit unnecessary personal data—such as contact lists or real-time location—users often experience privacy anxiety and distrust, which contribute to unfavorable evaluations of algorithmic recommendations [26]. Studies show that younger users are particularly sensitive to the transparency of personal data usage; once they perceive boundary violations, their emotional responses tend to be negative [43]. Moreover, when users realize that algorithms extend usage time or narrow content choices through autoplay, ranking mechanisms, or reward systems, they may experience psychological resistance and a sense of self-control failure [44,45]. These negative emotional and evaluative experiences can strengthen users' algorithm aversion. Hence, the following hypotheses are proposed:

H5. *Personalization positively influences algorithm dependence.*

H6. *Diversity positively influences algorithm dependence.*

H7. *Invasiveness positively influences algorithm aversion.*

H8. *Manipulateness positively influences algorithm aversion.*

2.4. *Affective Orientations and Continuance Intention*

Algorithm dependence, as a positively valenced reliance orientation toward recommendation algorithms, is expected to strengthen continuance intention. Users who rely on algorithms often experience convenience and enjoyment, which makes them more willing to continue obtaining content through algorithms and form stable usage patterns [46]. Thurman et al. [39] examined audience attitudes and trust toward “algorithmically curated news” and found that when users recognized the matching accuracy and convenience of algorithms, they were more inclined to rely on platform distribution. Similarly, research on intelligent voice assistants shows that the stronger users' emotional dependence on technology, the higher their long-term usage intentions [40]. Jo [46] also confirmed that positive affective factors in AI personal assistant usage are positively associated with continuance intention. Studies on short-form video platforms likewise indicate that dependence and reliance-related tendencies are important antecedents of sustained user engagement [36]. Thus, stronger psychological reliance on recommendation algorithms is associated with a greater willingness to continue using algorithm-supported content services.

In contrast, algorithm aversion represents a negatively valenced emotional and evaluative orientation toward recommendation algorithms. When users experience resentment, distrust, discomfort, or concern toward algorithms, these unfavorable orientations may

reduce their willingness to continue using algorithmic recommendations [47,48]. Negative evaluations of algorithmic recommendation can weaken users' acceptance and increase their tendency to disengage from recommendation systems. For instance, Lukoff et al. [42] demonstrated that autoplay and forceful recommendations diminish users' sense of autonomy and evoke negative experiences, thereby lowering acceptance and long-term motivation. Xie et al. [33], in a short-form video study, found that when users develop distrust or aversion toward algorithms, they adopt avoidance or obfuscation strategies, such as reducing usage frequency or deliberately interfering with recommendations. These findings suggest that stronger algorithm aversion is associated with lower continuance intention.

This discussion relates to the following hypotheses:

H9. *Algorithm dependence positively influences continuance intention.*

H10. *Algorithm aversion negatively influences continuance intention.*

2.5. Mediating Role of Affective Orientations

Within the CAC framework, affective orientations constitute an important intermediate mechanism linking users' cognitive evaluations to behavioral intentions. Cognitive evaluations of algorithmic features can shape users' positive or negative orientations toward recommendation algorithms, which in turn influence their continuance intention [49,50]. Specifically, benefit-based cognitions such as personalization and diversity can strengthen algorithm dependence as a positive reliance orientation, which in turn strengthens continuance intention. Conversely, risk-based cognitions such as invasiveness and manipulateness are more likely to strengthen algorithm aversion as a negative affective orientation, thereby suppressing continuance intention [23,26,29].

This mediating pathway has been validated across multiple technologies and contexts. In the case of TikTok, empirical evidence shows that users' perceptions of recommendation accuracy affect continuance intention through the mediating role of satisfaction and enjoyment [51]. In intelligent service robots, studies reveal that various cognitions influence usage intention via the mediation of trust [52]. In e-commerce environments, perceived value fosters platform attachment, which subsequently enhances purchase intention and stickiness [53]. Conversely, perceptions of privacy intrusion generate anxiety and distrust, reducing continuance intention [54]. Similarly, perceptions of manipulateness or restricted choice evoke psychological resistance, diminishing engagement [55]. Research on technostress also identifies fatigue and stress as negative emotions that mediate the link between overload and discontinuance intention, as observed in contexts such as WeChat [56,57]. Together, these findings indicate that cognitive evaluations of technology can influence subsequent behavioral intentions through affective and evaluative orientations toward the technology.

Therefore, this study proposes the following hypotheses:

H11. *Algorithm dependence mediates the relationship between personalization and continuance intention.*

H12. *Algorithm dependence mediates the relationship between diversity and continuance intention.*

H13. *Algorithm aversion mediates the relationship between invasiveness and continuance intention.*

H14. *Algorithm aversion mediates the relationship between manipulateness and continuance intention.*

3. Research Design

3.1. Methodology

The primary objective of this study is to examine the hypothesized relationships among users' cognition of algorithmic features, affective responses toward algorithms, and continuance intention, as well as to uncover the configurational mechanisms through which multiple conditions jointly lead to high continuance intention. The proposed research model is presented in Figure 1. Achieving this objective requires analytical tools capable of handling both linear relationships among variables and multiple conjunctural causation.

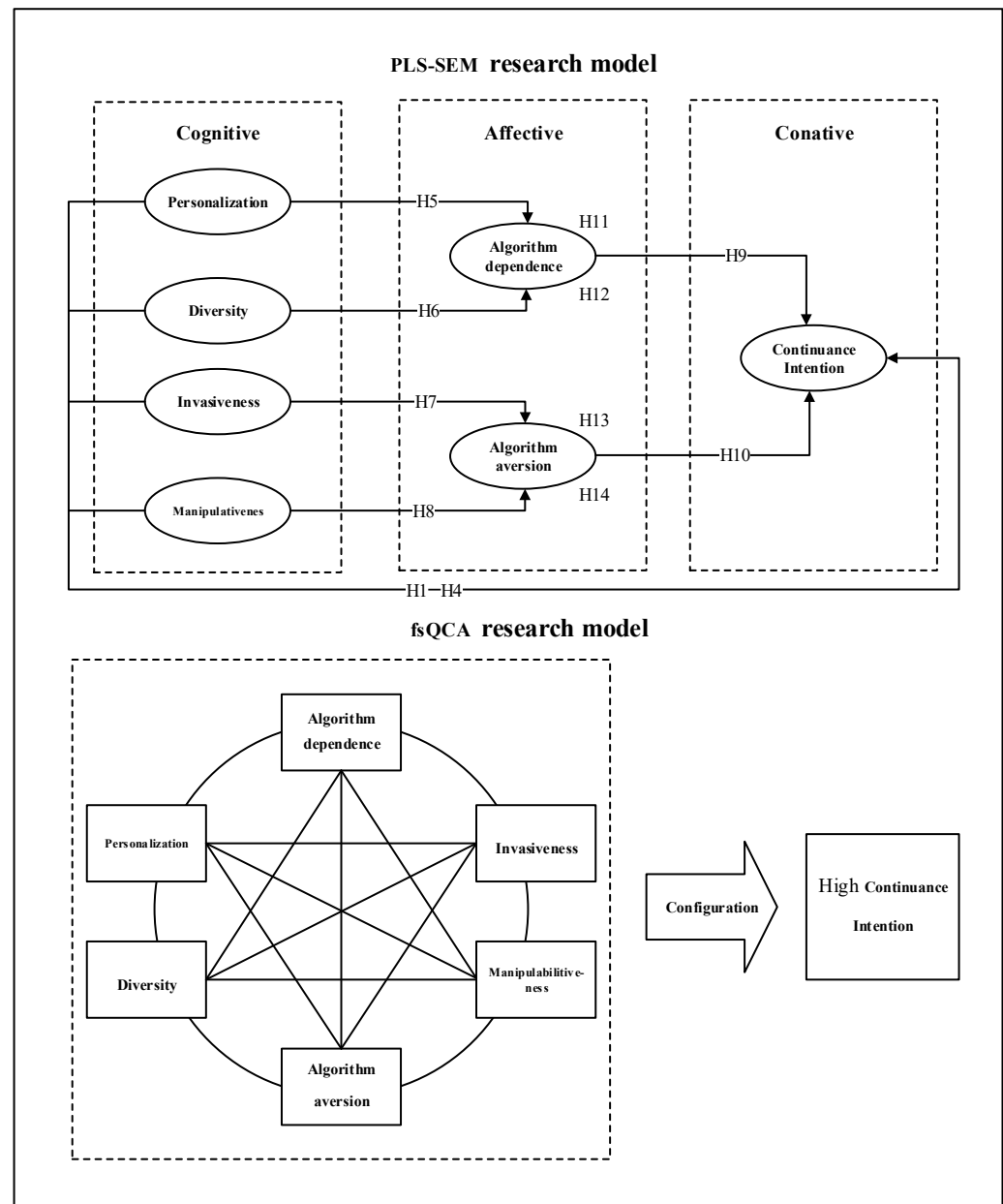


Figure 1. Research model.

PLS-SEM is employed as the key technique for testing direct and mediating effects, because the study adopts an explanatory–predictive orientation, seeking not only to estimate the proposed relationships but also to explain and predict variance in the endogenous constructs. As a variance-based structural equation modeling approach, PLS-SEM is particularly suitable when prediction and explained variance are central analytical objectives, while also allowing simultaneous assessment of the measurement and structural mod-

els [58]. Specifically, reliability and validity analyses of the measurement model (including composite reliability, Cronbach's α , convergent validity, and discriminant validity) are conducted, along with evaluations of path significance, R^2 , and out-of-sample predictive performance in the structural model, to assess the proposed relationships among the cognitive, affective, and conative constructs.

However, single linear regression analysis cannot adequately reveal mechanisms of "multiple conjunctural causation." Therefore, this study further applies fsQCA to examine configurational effects of antecedent conditions [59]. Cognitive variables (personalization, diversity, invasiveness, manipulateness) and affective variables (algorithm dependence, algorithm aversion) are treated as condition variables, enabling identification of multiple conjunctural paths leading to high continuance intention and unveiling the complex interaction patterns between cognition and affect.

3.2. Variable Measurement

This study involves seven constructs: personalization, diversity, invasiveness, manipulateness, algorithm dependence, algorithm aversion, and continuance intention. To ensure reliability and validity, established scales from prior studies were adopted, with contextual modifications and item reductions where appropriate. Because the original scales were developed in English, the items were translated into Chinese and then back-translated into English. The original and back-translated versions were compared through reconciliation meetings, and discrepancies in wording or meaning were discussed until semantic consistency was achieved. Subsequently, five scholars with expertise in e-commerce reviewed the translated items in terms of semantic clarity, construct relevance, and contextual appropriateness for short-form video recommendation. Their feedback was used to refine the wording and inform item-retention decisions while preserving the intended conceptual meaning of the original scales. All items were measured using a 7-point Likert scale (1 = "strongly disagree," 7 = "strongly agree"), with higher scores indicating stronger agreement. The measurement items and corresponding sources are listed in Table 1. The constructs were operationalized in accordance with their conceptual roles in the short-form video recommendation context. Personalization captures users' perceived preference-based tailoring of recommended content, encompassing the algorithm's ability to identify preferences, provide personally relevant content, and facilitate access to preferred videos. Diversity captures the perceived breadth and variation in recommendation outputs across content categories, themes, creators, and usage occasions. Invasiveness refers specifically to perceived intrusion into informational privacy boundaries associated with the platform's knowledge, use, and protection of users' personal information, whereas manipulateness captures perceived algorithmic influence over users' attention, viewing choices, and browsing autonomy. Continuance intention refers specifically to users' intention to continue engaging with algorithmically recommended videos through the focal platform's recommendation function.

Table 1. Questionnaire items.

Construct	Items	Source
Personalization	PE1: I think the short videos recommended by the platform match my personal interests.	[48]
	PE2: The platform's personalized recommendations make it easier for me to find content I like.	
	PE3: I believe the platform's algorithm can effectively capture my viewing preferences.	

Table 1. Cont.

Construct	Items	Source
Diversity	DI1: The videos recommended by the platform cover a variety of types.	[60,61]
	DI2: Each time I open the platform, the combination of recommended videos feels fresh.	
	DI3: The recommended videos display high diversity in terms of themes, creators, etc.	
Invasiveness	IN1: Sometimes I feel that the platform's recommendations invade my privacy.	[11,62]
	IN2: I think the platform knows too much about my viewing habits and personal information.	
	IN3: The platform's recommendations sometimes make me feel my personal data is being misused.	
	IN4: I am concerned about the platform's performance in protecting user privacy.	
Manipulativeness	MA1: I feel the platform's recommendation algorithm tries to guide me to watch specific videos.	[44,55]
	MA2: Sometimes I feel manipulated by the recommendation algorithm, losing my sense of autonomy in browsing.	
	MA3: The recommendations make me feel that my video choices are interfered with to some extent.	
	MA4: I think the platform sometimes pushes certain videos too aggressively.	
Algorithm dependence	AD1: I feel reassured when the platform's recommendation algorithm consistently understands my preferences.	[63]
	AD2: Without algorithmic recommendations, I would feel uncertain about discovering videos that I like.	
	AD3: I feel more inclined to accept videos recommended by the platform than to search for them myself.	
	AD4: I feel a growing reliance on the platform's recommendation algorithm when deciding what to watch next.	
Algorithm aversion	AA1: I sometimes feel annoyed or dissatisfied with the platform's recommendation algorithm.	[64,65]
	AA2: I think the algorithm goes too far in some respects, making me uncomfortable.	
	AA3: Certain algorithmic behaviors on the platform make me feel misled or deceived.	
	AA4: I feel worried and uneasy about the potential negative impacts of the platform's algorithm.	
Continuance intention	CI1: I am willing to actively check new recommended videos on the platform.	[10]
	CI2: I will continue to click and watch videos recommended by the platform.	
	CI3: I am willing to keep using the platform's recommendation function to access content.	
	CI4: Compared with other platforms, I prefer to watch videos recommended by this platform.	

3.3. Questionnaire Design and Data Collection

Data were collected using a non-probability recruitment strategy combining online recruitment and network-based snowball recruitment. Online respondents were recruited through the sample service provided by Tencent Questionnaire and received RMB 3 for completing the survey, whereas the network-based sample was recruited through the research team's social networks and subsequent referrals. Regardless of recruitment source, all respondents completed the same questionnaire through Tencent Questionnaire. The

study protocol was approved by the Ethics Committee of the School of Economics and Management, Xiamen University of Technology. Participation was voluntary, and respondents were informed that their responses would remain confidential and be used solely for academic purposes.

The survey was conducted between 21 September and 27 November 2024. A total of 733 questionnaires were collected, and responses with identical or highly patterned answers or excessively short completion times were excluded. After screening, 547 valid responses remained, including 282 from the online-recruitment channel and 265 from the network-based recruitment channel, yielding a valid response rate of 74.6%. Independent-samples t-tests were conducted to compare the two recruitment groups in terms of gender, age, and education. The results showed no significant differences between the two groups in these demographic characteristics.

Descriptive statistics for the 547 valid respondents are shown in Table 2. Among the sample, 265 were male (48.4%) and 282 were female (51.6%), indicating a relatively balanced gender distribution. Regarding age, 182 respondents (33.3%) were aged 20–29, 226 (41.3%) were aged 30–39, 82 (15.0%) were aged 40–49, and 57 (10.4%) were aged 50 and above, reflecting broad age coverage but a concentration in the 20–39 age range, consistent with the main demographic of short-form video users. Regarding education, 94 respondents (17.2%) had secondary vocational school, high school or below, 179 (32.7%) had junior college, 221 (40.4%) held a bachelor's degree, and 53 (9.7%) held a master's degree or above, reflecting diverse educational backgrounds.

Table 2. Descriptive analysis of respondents ($n = 547$).

Category	Group	Frequency	Percentage (%)
Gender	Male	265	48.4
	Female	282	51.6
Age	20–29	182	33.3
	30–39	226	41.3
	40–49	82	15.0
	50 and above	57	10.4
Education	Secondary vocational school, high school and below	94	17.2
	Junior college	179	32.7
	Bachelor's degree	221	40.4
	Master's degrees and above	53	9.7

4. Results

4.1. Common Method Bias Tests

Common method bias arises when consistent measurement methods introduce spurious correlations among variables, thereby threatening the validity of research findings. To assess the potential impact of common method bias, we conducted Harman's single-factor test, which is based on exploratory factor analysis. The logic is that if a single factor accounts for more than half of the total variance, then significant common method bias exists [66]. The questionnaire items converged into five factors with eigenvalues greater than 1. Without rotation, the first factor accounted for only 29.178% of the variance, far below the 50% threshold. Meanwhile, the cumulative variance explained by all factors reached 64.284%. However, Harman's single-factor test has been criticized for its limited sensitivity in detecting common method bias. Consequently, we also applied the unmeasured common method factor approach proposed by Liang et al. [67] as an additional assessment. Results (Table 3) showed that the average substantive explained variance was

0.705, whereas the average method-based variance was only 0.0016, yielding a ratio of approximately 438.773:1. All substantive factor loadings were significant, whereas none of the method-factor loadings was significant. Taken together with the Harman test, these results suggest that common method bias is unlikely to materially affect the findings.

Table 3. Common method factor analysis.

Constructs	Indicator	Substantive Factor Loading (R1)	R1 ²	Method Factor Loading (R2)	R2 ²
AA	AA1	0.861 *	0.741	0.013	0.000
	AA2	0.867 *	0.752	0.033	0.001
	AA3	0.870 *	0.757	−0.072	0.005
	AA4	0.863 *	0.745	0.025	0.001
AD	AD1	0.802 *	0.643	0.009	0.000
	AD2	0.795 *	0.632	0.028	0.001
	AD3	0.803 *	0.645	−0.022	0.000
	AD4	0.809 *	0.654	−0.015	0.000
CI	CI1	0.835 *	0.697	−0.054	0.003
	CI2	0.837 *	0.701	−0.016	0.000
	CI3	0.848 *	0.719	0.025	0.001
	CI4	0.835 *	0.697	0.045	0.002
DI	DI1	0.847 *	0.717	0.010	0.000
	DI2	0.770 *	0.593	−0.065	0.004
	DI3	0.794 *	0.630	0.053	0.003
IN	IN1	0.862 *	0.743	−0.028	0.001
	IN2	0.810 *	0.656	−0.034	0.001
	IN3	0.858 *	0.736	0.012	0.000
	IN4	0.860 *	0.740	0.047	0.002
MA	MA1	0.871 *	0.759	−0.108	0.012
	MA2	0.854 *	0.729	0.031	0.001
	MA3	0.849 *	0.721	0.027	0.001
	MA4	0.882 *	0.778	0.049	0.002
PE	PE1	0.873 *	0.762	0.009	0.000
	PE2	0.854 *	0.729	−0.002	0.000
	PE3	0.813 *	0.661	−0.008	0.000
Average			0.705		0.002

Note: * The level of significance is 0.05.

4.2. Assessment of Measurement Model

The measurement model is a core component of PLS-SEM, serving to evaluate whether observed variables effectively capture their latent constructs. This study adopted common indicators—including factor loadings, variance inflation factor (VIF), Cronbach's α , average variance extracted (AVE), and CR—to assess the measurement model's quality. As shown in Table 4, all item loadings exceeded the conventional threshold of 0.7, with the lowest loading reaching 0.784, confirming strong construct validity [68]. All VIF values were below 3 [69], indicating that multicollinearity was not a serious concern. The lowest Cronbach's α was 0.726, above the 0.7 benchmark [70], demonstrating acceptable internal consistency. CR values ranged from 0.846 to 0.923, well above the recommended 0.7 threshold Gefen et al. [71] confirming stability and reliability. Additionally, AVE values ranged from 0.643

to 0.748, exceeding the recommended cutoff of 0.50 Fornell and Larcker [72], thereby establishing satisfactory convergent validity for all constructs.

Table 4. Measurement model analysis results.

Constructs	Items	Loadings	VIF	α	CR	AVE
PE	PE1	0.868	1.949	0.803	0.884	0.717
	PE2	0.847	1.836			
	PE3	0.825	1.552			
DI	DI1	0.838	1.612	0.726	0.846	0.646
	DI2	0.784	1.350			
	DI3	0.789	1.440			
IN	IN1	0.862	2.289	0.869	0.911	0.719
	IN2	0.805	1.848			
	IN3	0.859	2.287			
	IN4	0.864	2.215			
MA	MA1	0.861	2.470	0.887	0.922	0.746
	MA2	0.860	2.263			
	MA3	0.848	2.192			
	MA4	0.885	2.607			
AD	AD1	0.808	1.687	0.815	0.878	0.643
	AD2	0.788	1.670			
	AD3	0.802	1.696			
	AD4	0.810	1.726			
AA	AA1	0.865	2.292	0.888	0.923	0.748
	AA2	0.866	2.362			
	AA3	0.865	2.408			
	AA4	0.865	2.303			
CI	CI1	0.842	1.979	0.859	0.905	0.703
	CI2	0.830	2.013			
	CI3	0.850	2.088			
	CI4	0.831	1.979			

Discriminant validity is another crucial standard for evaluating measurement models. This study employed both the Heterotrait–Monotrait ratio (HTMT) and the Fornell–Larcker criterion to test whether constructs are distinct and non-confounding. As shown in Table 5, HTMT values ranged from 0.045 to 0.759, significantly below the threshold of 0.85 proposed by Henseler et al. [73]. This indicates that the constructs maintained clear independence at the measurement level. Table 6 further presents the Fornell–Larcker criterion results. For each construct, the square root of AVE (on the diagonal, in bold) exceeded its correlations with other constructs, once again confirming discriminant validity [72].

Table 5. Discriminant validity: HTMT.

	PE	DI	IN	MA	AD	AA	CI
PE							
DI	0.742						
IN	0.093	0.058					
MA	0.184	0.074	0.755				
AD	0.662	0.759	0.052	0.045			
AA	0.210	0.096	0.741	0.752	0.086		
CI	0.677	0.633	0.151	0.228	0.664	0.224	

Table 6. Discriminant validity: Fornell–Larcker criterion.

	PE	DI	IN	MA	AD	AA	CI
PE	0.847						
DI	0.567	0.804					
IN	−0.076	−0.045	0.848				
MA	−0.156	−0.055	0.663	0.864			
AD	0.537	0.584	0.018	−0.006	0.802		
AA	−0.178	−0.074	0.653	0.671	−0.066	0.865	
CI	0.564	0.502	−0.131	−0.201	0.558	−0.195	0.839

Note: The diagonal of the matrix (boldface) is the square root of AVE.

4.3. Assessment of Structural Model

The structural model was assessed in terms of explained variance and out-of-sample predictive performance. R^2 was used to evaluate the proportion of variance explained in the endogenous constructs. In addition, PLSpredict was employed to assess out-of-sample predictive relevance. Q^2 predict values greater than zero indicate predictive relevance, while RMSE and MAE reflect prediction errors, with lower values indicating greater predictive accuracy [74,75].

As shown in Table 7, the R^2 values were 0.527 for AA, 0.404 for AD, and 0.476 for CI, indicating meaningful explanatory power. The corresponding Q^2 predict values were 0.518, 0.392, and 0.384, respectively, and were all above zero. The RMSE values ranged from 0.697 to 0.789, while the MAE values ranged from 0.524 to 0.604. These results indicate that the model demonstrates out-of-sample predictive relevance for all three endogenous constructs.

Table 7. Results of structural model analysis.

Constructs	R^2	Q^2	RMSE	MAE
AA	0.527	0.518	0.697	0.524
AD	0.404	0.392	0.783	0.577
CI	0.476	0.384	0.789	0.604

In this study, we further conducted hypothesis testing using the bootstrapping method. Table 8 presents the regression coefficients and significance levels of the direct effects.

First, we tested the impact of algorithmic features on continuance intention. Results showed that personalization and diversity significantly and positively influenced continuance intention ($\beta = 0.259$, $p < 0.001$; $\beta = 0.149$, $p < 0.05$), supporting H1 and H2. Manipulativeness significantly and negatively influenced continuance intention ($\beta = -0.151$, $p < 0.05$), supporting H4. Although invasiveness negatively influenced continuance intention ($\beta = -0.052$), the effect was nonsignificant ($p > 0.05$), thus H3 was not supported.

Table 8. Results of hypotheses validation.

Hypothesis	Path	Std. Beta	<i>t</i> Value	<i>p</i> Value	VIF	Results
H1	PE → CI	0.259 *	4.370	<0.001	1.733	Support
H2	DI → CI	0.149 *	2.571	0.010	1.791	Support
H3	IN → CI	−0.052	0.960	0.337	2.172	Not Support
H4	MA → CI	−0.151 *	2.904	0.004	2.244	Support
H5	PE → AD	0.302 *	5.323	<0.001	1.474	Support
H6	DI → AD	0.413 *	7.401	<0.001	1.474	Support
H7	IN → AA	0.372 *	6.719	<0.001	1.782	Support
H8	MA → AA	0.424 *	7.528	<0.001	1.782	Support
H9	AD → CI	0.335 *	6.260	<0.001	1.714	Support
H10	AA → CI	0.004	0.077	0.939	2.210	Not Support
Gender	Gender → CI	0.062	0.989	0.323	1.039	—
Age	Age → CI	−0.114 *	2.779	0.005	1.159	—
Education	Education → CI	0.079 *	2.271	0.023	1.097	—

Note: * The level of significance is 0.05.

Second, we tested the impact of algorithmic features on algorithm dependence and algorithm aversion. Results showed that personalization and diversity significantly and positively influenced algorithm dependence ($\beta = 0.302$, $p < 0.001$; $\beta = 0.413$, $p < 0.01$), supporting H5 and H6. Invasiveness and manipulateness significantly and positively influenced algorithm aversion ($\beta = 0.372$, $p < 0.001$; $\beta = 0.424$, $p < 0.01$), supporting H7 and H8.

Finally, we examined the impact of algorithm dependence and algorithm aversion on continuance intention. Results indicated that algorithm dependence significantly and positively influenced continuance intention ($\beta = 0.335$, $p < 0.001$), supporting H9. Algorithm aversion showed a small positive but statistically nonsignificant coefficient ($\beta = 0.004$, $p > 0.05$); therefore, H10 was not supported.

This study further verified the mediating effects proposed in the model by examining the significance levels of the outputs and the corresponding 95% confidence intervals. The judgment criterion was as follows: if the *p*-value was less than 0.05 and the 95% confidence interval did not include zero, then the mediating effect was considered supported [76]. As shown in Table 9, the mediation path PE → AD → CI had a confidence interval of [0.057, 0.155], which did not include zero, with $p < 0.001$; thus, H11 was supported. The mediation path DI → AD → CI yielded a confidence interval of [0.082, 0.210], which also did not include zero, with $p < 0.001$; hence, H12 was supported. In contrast, the mediation paths IN → AA → CI and MA → AA → CI had confidence intervals of [−0.040, 0.042] and [−0.044, 0.049], respectively, both including zero. Their corresponding *p*-values (0.940 and 0.939) exceeded the 0.05 threshold. Therefore, H13 and H14 were not supported.

Table 9. Results of indirect effect.

Hypothesis	Path	Std Beta	T Statistics	Bias-Corrected Percentile 95% CI		<i>p</i> -Value	Results
				LOWER	UPPER		
H11	PE → AD → CI	0.101 *	4.025	0.057	0.155	<0.001	Support
H12	DI → AD → CI	0.139 *	4.183	0.082	0.210	<0.001	Support
H13	IN → AA → CI	0.002	0.076	−0.040	0.042	0.940	No Support
H14	MA → AA → CI	0.002	0.076	−0.044	0.049	0.939	No Support

Note: * The level of significance is 0.05.

4.4. Fuzzy-Set Qualitative Comparative Analysis Results

In the above analysis, this study employed PLS-SEM to estimate the hypothesized relationships among latent variables. While PLS-SEM excels at quantifying path coefficients, CI is often driven by interactions and combinations of multiple conditions. Traditional structural models are limited in capturing causal complexity and equifinality. To address this limitation, we further adopted fsQCA [59], which—under a configurational lens—systematically examines how different combinations of conditions jointly produce CI and thereby uncovers more complex mechanisms.

Calibration is a key step in fsQCA that transforms raw observations into set-membership scores to support configurational analysis. Concretely, we first computed the sample means of all variables and then followed Ragin's [77] direct calibration strategy. Using the 95th, 50th, and 5th percentiles as anchors for full membership, crossover, and full non-membership, respectively, we mapped raw values into the [0, 1] interval. The specific calibration anchors for all constructs are reported in Table A1.

Within the fsQCA framework, necessity analysis precedes configurational modeling and tests whether any single condition (and its negation) is indispensable for the outcome. We evaluated all antecedent conditions and their negations, adopting 0.90 as the necessity consistency threshold [59]. As shown in Table 10, none of the conditions reached 0.90, indicating that no single necessary condition exists for CI. We therefore proceeded to examine the sufficiency of condition combinations.

Table 10. Results of Necessity Analysis.

Condition	Consistency	Coverage
PE	0.746	0.837
~PE	0.595	0.620
DI	0.778	0.806
~DI	0.554	0.627
IN	0.677	0.729
~IN	0.649	0.705
MA	0.731	0.729
~MA	0.621	0.734
AD	0.807	0.830
~AD	0.523	0.596
AA	0.680	0.696
~AA	0.633	0.725

In the configurational analysis, we specified sets of conditions featuring presence/absence and different combinations, and then used fuzzy-set logic and Boolean algebra to assess their relationships with CI. We computed consistency as an indicator of sufficiency and coverage as an indicator of empirical relevance. Following Fiss [78], we set the consistency threshold at 0.80, the PRI-consistency threshold at 0.70, and the case frequency threshold at 3. As reported in Table 11, four sufficient configurations were identified, with configuration consistency values ranging from 0.922 to 0.943. The overall solution consistency was 0.912, and the solution coverage was 0.671, indicating that the identified configurations exhibit high consistency and substantial empirical coverage.

Across the four configurations, AD appears as a core condition in all solutions, indicating its stable role within the sufficient configurations associated with high CI. PE and DI also emerge as core conditions in several configurations, whereas IN, MA, and AA vary across different configurational contexts. Based on their structural characteristics, the four configurations can be grouped into three dependence-maintenance pathways: experience-reinforced dependence, risk-buffered dependence, and risk-tolerant dependence.

Table 11. Results of Configurational Analysis.

Configurations	M1	M2	M3	M4
PE	●	●	●	
DI	●		●	●
IN		⊗	●	●
MA	●	⊗		●
AD	●	●	●	●
AA		⊗	●	●
Consistency	0.941	0.942	0.943	0.922
Raw coverage	0.495	0.365	0.423	0.469
Unique coverage	0.046	0.109	0.007	0.057
Solution consistency			0.912	
Solution coverage			0.671	

Note: ●/● denote presence; ⊗/⊗ denote absence; ●/⊗ indicate core conditions; ●/⊗ indicate peripheral conditions; blanks denote that the condition may be either present or absent in that configuration.

First, Configuration 1 (PE*DI*MA*AD) represents the experience-reinforced dependence pathway. In this configuration, PE, DI, and AD are core conditions, while MA is a peripheral condition. The simultaneous presence of personalization and diversity indicates that users perceive the recommendation system as both personally relevant and sufficiently varied. Together with algorithm dependence, these positive algorithm-related perceptions form a sufficient configuration associated with high CI, even when some degree of manipulateness is present.

Second, Configuration 2 (PE*~IN*~MA*AD*~AA) represents the risk-buffered dependence pathway. PE, the absence of IN, and AD constitute core conditions, while the absence of MA and AA are peripheral conditions. This configuration indicates that high CI can emerge when personalization and algorithm dependence coexist with low invasiveness, accompanied by relatively weak perceptions of manipulateness and algorithm aversion. This pattern suggests that the attenuation of negative algorithm-related perceptions may coexist with personalized recommendation and dependence in configurations associated with high CI.

Third, Configurations 3 and 4 represent the risk-tolerant dependence pathway. Configuration 3 (PE*DI*IN*AD*AA) combines the core presence of PE, DI, IN, and AD with the peripheral presence of AA. Configuration 4 (DI*IN*MA*AD*AA) combines the core presence of DI, IN, and AD with the peripheral presence of MA and AA. These two configurations are particularly noteworthy because algorithm dependence and algorithm aversion coexist within sufficient configurations associated with high CI. This indicates that the presence of algorithm aversion does not necessarily preclude high continuance intention when algorithm dependence remains a core condition and is accompanied by supportive conditions such as personalization or diversity.

To assess robustness, three additional fsQCA analyses were conducted. Raising the consistency threshold to 0.85 reproduced the same four configurations [79] (Table A2). Increasing the case frequency threshold from 3 to 4 again yielded four configurations, with AD remaining present across all configurations and AD and AA continuing to coexist in two configurations associated with high CI (Table A3). Finally, alternative calibration anchors were employed following recent fsQCA studies [80,81], and the central role of AD and the overall dependence-maintenance pattern remained stable (Table A4). Overall, the main configurational findings remained substantively stable across alternative analytical specifications.

5. Discussion

Grounded in the CAC framework, this study employed direct effect analysis, mediation testing, and configurational analysis to systematically examine how short-form video recommendation algorithms shape users' CI. The key findings are discussed below.

5.1. Interpreting the Findings Through the Cognitive-Affective-Conative Lens

The results show that PE and DI exert significant positive effects on CI, consistent with prior studies [30,82,83]. This finding reaffirms that algorithmic recommendation systems can enhance user experience and continued engagement by precisely matching user interests and providing a rich variety of content. Personalization reduces users' information-filtering costs, while diversity mitigates fatigue from content narrowness; together, they encourage sustained behavioral intention.

In addition, MA negatively affects CI, echoing Cheng and Peng [55] and indicating users' psychological resistance to perceived manipulation. By contrast, the negative impact of IN on CI was not statistically significant, diverging from prior research. Previous studies have suggested that privacy intrusion directly reduces usage intention [84–86]. In short-form video use, privacy concerns may coexist with the convenience, relevance, and entertainment benefits provided by algorithmic recommendation, reflecting a possible gap between privacy concerns and continued platform use. Repeated exposure to data collection practices may also normalize such practices and reduce their salience in continuance decisions. Moreover, differences in algorithmic literacy and perceived privacy-control options may shape how users evaluate invasiveness and incorporate privacy concerns into their usage decisions. These factors suggest that the relationship between invasiveness and CI may vary across users and platform-use contexts.

5.2. Mediating Roles of Algorithm Dependence and Algorithm Aversion

Mediation analysis reveals different roles of AD and AA in the relationships between algorithm-related cognition and CI. AD significantly mediates the effects of both PE and DI on CI, whereas AA's mediation effect is non-significant. This pattern highlights the differentiated roles of the two affective orientations in the cognition–affect–conation process. AD reflects a positively valenced reliance orientation through which favorable algorithmic perceptions are associated with continued use. When users perceive recommendation algorithms as relevant and diverse, they are more likely to rely on the platform for content discovery and information filtering, thereby strengthening CI. This finding is consistent with research showing that algorithm dependence develops as users obtain gratification from algorithm-supported services and increasingly rely on them in their usage process [63].

By contrast, AA neither significantly predicts CI nor mediates the effects of IN and MA. AA reflects a negatively valenced emotional and evaluative orientation toward recommendation algorithms, encompassing feelings such as annoyance, discomfort, dissatisfaction, and unease. Such an orientation is conceptually different from overt algorithm rejection or avoidance, which involves a behavioral tendency to discount or refrain from using algorithmic recommendations [64,65,87]. The nonsignificant relationship between AA and CI suggests that unfavorable evaluations of recommendation algorithms do not necessarily correspond to reduced continuance intention. Negative affect may remain primarily evaluative when its behavioral intensity is limited, while habitual platform use, functional reliance on recommendation systems, switching costs, or limited alternatives may weaken its relationship with discontinuance. This pattern points to a possible evaluative–behavioral gap in which unfavorable algorithm evaluations coexist with continued use. This distinction is also consistent with research showing that negative reactions to recommendation algorithms can take different forms, including psychological resistance and behavioral

avoidance [33,55], and that these responses should not be treated as interchangeable. In algorithmic environments, users may therefore experience a disjunction between affective orientation and behavioral intention: they may evaluate algorithms negatively yet continue usage due to functional dependence.

5.3. Configurational Analysis

The configurational analysis identified three dependence-maintenance pathways to high CI, reflecting the complexity of user decision-making. The experience-reinforced dependence pathway indicates that favorable algorithmic perceptions combined with algorithm dependence are sufficient for high CI, whereas the risk-buffered dependence pathway shows that high CI can also arise when negative algorithm-related perceptions are relatively weak. Notably, although algorithm aversion shows no significant net effect on continuance intention in the PLS-SEM results, it coexists with algorithm dependence and high continuance intention in the two configurations of the risk-tolerant dependence pathway. This suggests that aversion may fail to translate into behavioral disengagement when algorithm dependence and perceived benefits, such as personalization and diversity, remain sufficiently strong: the functional reliance and gratification that sustain usage may outweigh negative evaluations, such that aversion is tolerated rather than acted upon. High continuance intention is thus maintained not by the absence of aversion, but by the dominance of dependence over aversion within users' overall configurational profile. This coexistence captures the "Cannot Stop, Yet Resent It" phenomenon highlighted in this study and suggests that whether algorithm aversion leads to disengagement depends on the strength of the coexisting dependence-supporting conditions.

6. Implications, Limitations, and Future Research

6.1. Theoretical Contributions

First, this study extends the application of the affective stage of the CAC framework to algorithm-mediated platform use by distinguishing algorithm dependence and algorithm aversion as two affective orientations toward recommendation algorithms. Algorithm dependence reflects a positively valenced reliance orientation, whereas algorithm aversion reflects a negatively valenced emotional and evaluative orientation. This distinction helps explain how users' cognitive evaluations of algorithmic affordances and risks may be translated into different affective orientations, which in turn shape continuance intention. In doing so, this study provides a more specific account of the cognition-affect-conation process in algorithm-mediated platform use.

Second, this study reveals differentiated relationships between the two affective orientations and algorithmic continuance. The findings show that algorithm dependence significantly mediates the effects of positive algorithmic perceptions on continuance intention, whereas algorithm aversion neither significantly predicts continuance intention nor mediates the effects of negative algorithmic perceptions. This pattern suggests that positively valenced reliance and negatively valenced aversion do not relate to continuance intention in symmetrical ways. In the short-form video context, recommendation algorithms are deeply embedded in everyday content access and provide immediate gratification. Under such conditions, negative emotional and evaluative orientations may remain salient without necessarily translating into reduced continuance intention, whereas psychological reliance on recommendation algorithms is more closely associated with continued use. This finding adds nuance to the CAC framework by showing that differently valenced affective orientations can exhibit different relationships with subsequent conative intention.

Third, this study uses the configurational findings to identify three dependence-maintenance pathways underlying high continuance intention: experience-reinforced

dependence, risk-buffered dependence, and risk-tolerant dependence. These mechanisms show that algorithm dependence is not only an affective orientation in the cognition–affect–conation process, but also a common anchoring condition across different configurations leading to high continuance intention. High continuance intention may be reinforced by positive algorithmic experiences, stabilized when negative algorithm-related perceptions are limited, or maintained even when certain negative conditions coexist with positive algorithmic perceptions. This configurational explanation extends the understanding of algorithmic continuance from a single linear pathway to multiple dependence–maintenance pathways.

6.2. Practical Implication

Platforms should optimize positive algorithmic experiences by improving both personalization and diversity. Personalization helps users access content that matches their interests, while diversity prevents repetitive recommendations and sustains novelty. Rather than simply increasing recommendation intensity, platforms should provide adjustable personalization, exploration-oriented modes, and diverse adjacent or cross-domain content so that users can actively shape their recommendation environment. This approach can preserve the benefits of algorithmic assistance while fostering functional, controllable reliance rather than excessive dependency.

Platforms should reduce negative algorithmic perceptions, especially perceived manipulateness and privacy-related concerns. Since perceived manipulateness negatively affects continuance intention, platforms should avoid designs that undermine perceived autonomy, including excessive push notifications, aggressive autoplay, or interaction patterns intended primarily to prolong use. Greater emphasis should instead be placed on meaningful user control through features such as “not interested,” “reduce similar content,” recommendation explanations, and adjustable recommendation settings. Although invasiveness did not show a significant direct relationship with CI, transparent data practices and accessible privacy controls remain important components of responsible algorithm design and long-term user trust.

More broadly, platform governance should distinguish healthy functional reliance on recommendation algorithms from problematic dependency or compulsive use. The configurational findings show that high continuance intention can emerge under different combinations of positive and negative algorithm-related conditions, with algorithm dependence appearing as a core condition across the identified configurations. Accordingly, algorithm dependence should not be treated as an unqualified retention objective. Platforms should provide recommendation-reset functions, usage-management tools, and appropriate friction against compulsive consumption, while incorporating user-welfare indicators such as perceived control, autonomy, and balanced use alongside conventional engagement metrics. These measures can support sustainable engagement while balancing user experience, user welfare, and responsible platform governance.

6.3. Limitations and Future Research

Despite its valuable contributions, this study has several limitations. First, the generalizability of our findings is bounded by the sampling context and recruitment approach. The data were collected from 547 short-form video users in China through non-probability online and snowball recruitment, which limits the representativeness of the sample. Although the high penetration of short-form video use in China offers a meaningful setting for examining deeply embedded algorithmic recommendation, users’ perceptions of algorithmic personalization, privacy, manipulation, dependence, and aversion may differ across countries, cultures, platforms, and regulatory environments—for instance, privacy expectations

and tolerance for data collection may vary under different data-protection regimes. Our findings should therefore be generalized to other populations and settings with caution, and future research could employ probability-based samples and conduct cross-country or cross-platform comparisons to test the boundary conditions of the proposed framework. Second, the cross-sectional design limits the ability to establish temporal ordering among the variables and to capture the dynamic evolution of user–algorithm interactions; therefore, alternative directional relationships among cognition, affective orientations, and continuance intention cannot be excluded. Future research may adopt longitudinal designs to track changes in users’ perceptions and behaviors toward algorithms over time, thereby better revealing proposed mechanisms and long-term effects. Finally, the study mainly focuses on algorithmic features and user emotional responses, while the moderating roles of individual differences, contextual factors, and platform-level environments are not fully considered. Future studies could incorporate moderators such as digital literacy, privacy concerns, and platform-specific policies (e.g., push-notification settings, algorithm audits) to explore heterogeneous responses across different groups and contexts.

6.4. Conclusions

This study examined the relationships among users’ cognitive evaluations of short-form video recommendation algorithms, algorithm dependence, algorithm aversion, and continuance intention. The PLS-SEM results show that personalization and diversity are positively associated with continuance intention and exert significant indirect effects through algorithm dependence, whereas manipulateness is negatively associated with continuance intention. Invasiveness and algorithm aversion show no significant direct relationships with continuance intention. The fsQCA results further identify three dependence-maintenance pathways associated with high continuance intention, with algorithm dependence appearing as a core condition across all four configurations. In two risk-tolerant configurations, algorithm dependence and algorithm aversion coexist alongside other algorithm-related conditions, reflecting a form of the “Cannot Stop, Yet Resent It” phenomenon. Overall, the findings suggest that continued engagement with short-form video recommendation systems is closely related to users’ reliance on algorithmic recommendations, while unfavorable evaluations do not necessarily translate into reduced continuance intention. They also show that high continuance intention can emerge through different combinations of positive and negative algorithm-related perceptions and affective orientations.

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Appendix A

Table A1. Calibration Anchors.

Construct	Full Membership (95th)	Crossover (50th)	Full Non-Membership (5th)
PE	7.000	5.667	3.333
DI	6.667	5.000	3.000
IN	6.750	5.250	2.250
MA	6.925	5.250	2.000
AD	6.750	5.000	3.325
AA	6.500	4.750	2.000
CI	7.000	5.250	2.825

Table A2. Robustness Test: Consistency Threshold = 0.85.

Configurations	M1	M2	M3	M4
PE	●	●	●	
DI	●		●	●
IN		⊗	●	●
MA	●	⊗		●
AD	●	●	●	●
AA		⊗	●	●
Consistency	0.941	0.942	0.943	0.922
Raw coverage	0.495	0.365	0.423	0.469
Unique coverage	0.046	0.109	0.007	0.057
Solution consistency			0.912	
Solution coverage			0.671	

Note: ●/● denote presence; ⊗/⊗ denote absence; ●/⊗ indicate core conditions; ●/⊗ indicate peripheral conditions; blanks denote that the condition may be either present or absent in that configuration.

Table A3. Robustness Test: Frequency Cutoff = 4.

Configurations	M1	M2	M3	M4
PE	●	●	●	
DI		●	●	●
IN	⊗		●	●
MA	⊗	●		●
AD	●	●	●	●
AA	⊗	⊗	●	●
Consistency	0.942	0.961	0.943	0.922
Raw coverage	0.365	0.328	0.423	0.469
Unique coverage	0.109	0.034	0.007	0.057
Solution consistency			0.914	
Solution coverage			0.659	

Note: ●/● denote presence; ⊗/⊗ denote absence; ●/⊗ indicate core conditions; ●/⊗ indicate peripheral conditions; blanks denote that the condition may be either present or absent in that configuration.

Table A4. Robustness Test: Alternative Calibration Anchors (95th/45th/5th Percentiles).

Configurations	M1	M2	M3
PE	●	●	●
DI	●		●
IN		⊗	●
MA	●	⊗	
AD	●	●	●
AA		⊗	●
Consistency	0.931	0.941	0.932
Raw coverage	0.524	0.364	0.462
Unique coverage	0.045	0.115	0.010
Solution consistency		0.920	
Solution coverage		0.654	

Note: ●/● denote presence; ⊗/⊗ denote absence; ●/⊗ indicate core conditions; ●/⊗ indicate peripheral conditions; blanks denote that the condition may be either present or absent in that configuration.

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