A Study on the Impact Mechanism of Short Video Recommendation Algorithms on User Content Engagement Duration from a Bidirectional Construction Perspective: A Case Study of Douyin's Hot Search Trends

Chenxi Yang
King's College London, London, SW10 2RL, United Kingdom

Abstract: In the context of algorithm-dominated content distribution on short-video platforms, user engagement duration serves not only as a core performance metric for platforms but also as a key indicator of bidirectional interaction between users and algorithms. Existing research predominantly focuses on the unidirectional shaping of user behavior by algorithms, lacking systematic exploration of users counter-regulation of algorithmic behavior. This study adopts the bidirectional construction theory pas its framework, employs TikTok's trending topics as the research scenario, and utilizes a mixed methods approach combining quantitative and qualitative analysis-through questionnaire surveys, in-depth interviews, and statistical analyses using SPSS and NVivo-to investigate the bidirectional influence mechanisms between short-video recommendation algorithms and user content engagement duration. The findings reveal that TikTok's collaborative filtering and traffic-weighted mechanisms significantly impact user engagement duration; user behaviors such as full viewing, liking, swiping away, and negative feedback constitute core signals driving algorithmic iteration; and users with varying algorithmic literacy exhibit distinct differences in engagement patterns and algorithmic compliance strategies. By constructing a closed-loop model of "algorithm–user–algorithm", this study addresses the unidirectional limitations of existing theories and provides practical insights for platform algorithm optimization, trending content management, and algorithmic ethics governance.

Keywords: Bidirectional Construction; Short Video Recommendation Algorithms; Engagement Duration; TikTok Trending Topics; Algorithmic Compliance; Human-Computer Interaction

1. Research Origin and Current Domestic and International Research Status

1.1 Research Significance

1.1.1 Theoretical significance

This study employs the two-way construction theory as its core analytical framework, integrating algorithmic technology, user behavior, and platform operations into a unified system to establish a bidirectional influence model between short video recommendation algorithms and user content engagement duration. Current academic research predominantly focuses on the algorithm's unidirectional driving effect on users, with limited exploration of how user behavior inversely shapes algorithmic iteration[5-7]. By using content engagement duration as a quantifiable and traceable behavioral metric and incorporating both the "algorithm-influencing-user" and "user-taming-algorithm" pathways, this paper fills gaps in existing research regarding theoretical integration and bidirectional interaction analysis, thereby enriching the human-computer interaction research framework within computational communication studies[2,8].

1.1.2 Practical significance

The study focuses on the highly timely and attention-grabbing scenario of TikTok's trending topics, analyzing the underlying logic by which algorithms drive user engagement and how users, in turn, reshape algorithms[6]. Its conclusions provide empirical evidence for short-video platforms to optimize algorithm design and enhance the efficiency of trending content operations. Additionally, the research findings offer actionable strategies for platforms to balance user experience, content quality, and

commercial objectives, while providing practical solutions to address algorithmic ethical dilemmas such as information cocooning and excessive immersion[9-13].

1.2 Current Research Status Domestically and Internationally

1.2.1 Current status of domestic research

Domestic research on short video algorithms generally follows the developmental trajectory of "technical logic → psychological mechanisms → scenario applications." At the algorithmic technology level, academic discussions have focused on the TikTok algorithm architecture and optimization strategies, demonstrating that personalized recommendations reduce user selection costs, multimodal feature extraction enhances content appeal, and real-time feedback mechanisms strengthen user immersion[1,3]. At the user engagement behavior level, algorithmic perception, content quality, and emotional value are key influencing factors; content with high emotional value stimulates dopamine secretion, driving sustained viewing[4]. At the algorithm-user interaction level, some studies have adopted a bidirectional perspective, highlighting that user behaviors such as dwell time, completion rates, and likes constitute core feedback signals, forming a closed-loop system of "recommendation → engagement → re-recommendation"[5,7].

1.2.2 Current state of international research

International research places greater emphasis on modeling algorithmic principles, quantitative analysis of user behavior, and ethical reflections on algorithms, establishing a research framework of "technical modeling → empirical analysis → ethical scrutiny." In the field of algorithmic technology, scholars have proposed the Content-Centric Attention Model (SCAM), which employs multi-objective modeling to balance click-through rate and user engagement metrics[14]. In user behavior studies, eye-tracking experiments and EEG research demonstrate that the approximately 2.8-second shot transition rhythm in short videos aligns with the human attention span recovery cycle, with algorithms utilizing a "variable-rate reinforcement" mechanism to encourage sustained user engagement[10]. In algorithmic ethics, scholarly focus centers on algorithmic bias and information cocooning, while findings indicate that selective exposure and active search behaviors can mitigate these limitations to some extent[12,15].

1.2.3 Literature review

Existing research exhibits three notable limitations: first, insufficient theoretical integration, lacking a systematic framework centered on the bidirectional construction theory; second, inadequate scenario focus, with relatively scarce micro-level empirical studies on TikTok's trending topics; third, weak research on reverse shaping mechanisms, with insufficient exploration of how user engagement duration inversely influences algorithm iteration. This study directly addresses these gaps, achieving breakthroughs in theory, scenario, and research perspective[1-7].

2. Research Design: Objectives, Content, and Core Questions

2.1 Research Objectives

(1) Develop a theoretical model that simultaneously models the short-video recommendation algorithm and user content engagement duration, quantitatively analyzing the strength and pathways of their bidirectional interactions.

(2) Reveal how user behaviors such as watching to the end, liking, swiping away, and negative feedback under TikTok's trending scenarios reshape the algorithmic iteration strategy.

(3) Provide actionable recommendations for optimizing platform algorithm design, enhancing the efficiency of trending topic management, and balancing user experience with commercial objectives.

2.2 Research Content

The core question of this study is: How does the TikTok trending recommendation algorithm affect users' content viewing duration, and how do users actively adapt the algorithm through behavioral strategies to align with their preferences?

It comprises three major sub-problems:

(1) How do the collaborative filtering mechanism and traffic-weighting rules in TikTok's trending features affect user dwell time?

(2) To what extent do user actions such as liking, swiping away, and negative feedback correct and refine algorithmic recommendations?

(3) What differences exist in user engagement patterns and algorithm adaptation strategies between individuals with varying levels of algorithmic literacy and usage habits?

2.3 Key Issues to Be Addressed

(1) Quantifiable measurement of bidirectional influence: Designing effective metrics and statistical models to simultaneously capture algorithm-driven engagement and user-driven algorithm iteration.
(2) Adaptability to trending scenarios: The research approach is designed to address the characteristics of trending topics-high timeliness, concentrated content, and strong attention aggregation.
(3) The deep mechanism of user conditioning: Revealing the subjective cognition, emotional motivations, and algorithmic imagination underlying behaviors through qualitative methods.

3. Research Methods and Technical Approach

3.1 Research Methods

This study employs a mixed methods approach, with quantitative research as the core and qualitative research as a supplement, integrating empirical modeling, statistical analysis, content analysis, and in-depth interviews.
•Quantitative Method: Using SPSS, we conducted descriptive statistics, correlation analysis, multiple linear regression, and lag effect analysis to precisely calculate the bidirectional influence coefficients between the algorithm and user dwell time.
•Qualitative Method: Through semi-structured in-depth interviews and content coding, this study employs the NVivo three-level coding refinement algorithm across three dimensions-user behavior, two-way interaction, and underlying mechanisms-to uncover the deep-seated mechanisms behind behaviors.

3.2 Technical Approach

Literature review and theoretical framework development → Research design and variable definition → Data collection (platform data + questionnaire + interviews) → Data analysis (quantitative analysis using SPSS + qualitative analysis using NVivo) → Model construction and mechanism elucidation → Conclusions and recommendations.

3.3 Research Plan

(1) Content Sampling: Fifty trending videos from Douyin's search results over the past three months were randomly selected, covering four major categories: society, entertainment, knowledge, and daily life.
(2) User sampling: A stratified sampling method was employed based on gender, age, usage duration, and city tier; 10 valid questionnaires were distributed and collected.
(3) In-depth Interview: Five users with significantly distinct behavioral characteristics were selected from the valid sample for semi-structured interviews.
(4) Quantitative Analysis: SPSS was used for descriptive statistics, correlation analysis, regression analysis, and lag effect testing.
(5) Qualitative analysis: NVivo three-level coding identifies core themes and mechanisms of action.
(6) Model Integration: Developing an algorithm for a two-way influence mechanism between users.

3.4 Feasibility Analysis

(1) Data feasibility: The open data interface of TikTok and third-party analysis tools enable access to platform data, while questionnaire and interview data can be independently collected through online channels.
(2) Methodological Feasibility: The SPSS and NVivo tools are well-established, and researchers possess fundamental operational skills. The mixed methods approach is widely adopted in communication studies[2,4].
(3) Resource feasibility: The sample size (50 videos + 10 users + 5 interviewees) aligns with undergraduate/masters research timelines, ensuring the task can be completed on schedule.
(4) Theoretical feasibility: The two-way construction theory, algorithmic recommendation theory, and user participation theory are all well-supported by substantial literature[1,5,7].

4. Questionnaire Data and Quantitative Analysis Results

This study distributed a total of 10 questionnaires, achieving a 100% valid response rate. The sample included users with diverse genders, ages, usage durations, and trending topic viewing frequencies. The survey data are summarized in the table 1.
Based on the aforementioned questionnaire data, statistical analysis using SPSS yielded the following key quantitative findings:
(1) The algorithm recommendation perception

shows a significant positive correlation with average dwell time; users with higher perception are more likely to develop consistent viewing habits[4,8].

(2) The completion rate and swipe-out rate together form the algorithm's most critical feedback signals, significantly influencing the weight of subsequent recommended content[3,5].

(3) Frequent users are more susceptible to information cocoons and tend to shape algorithms through active searching and deliberate consumption of lengthy content[9,12,15].

(4) The timeliness and topicality of trending content have significantly increased user engagement duration, yet the high level of immersion also carries risks associated with excessive usage[6,10,11].

Table 1. Valid Sample Data from the TikTok User Questionnaire Survey

User ID	sex	age	Daily average TikTok usage time	Search for trending topics frequency	Algorithm recommendation awareness(1-5)	Content richness perception (1-5)	Average dwell-time per trending topic (seconds)	Video completion rate	Like Rate	Withholding Rate	Negative feedback frequency (1-5)	Active search behavior (1-5)	Intentional scrolling through long content (1-5)	Information Cocoon Perception (1-5)	Overly-immersive perception (1-5)
U01	man	Ages 31–40	1-2h	Once daily	4	4	83	0.79	0.39	0.60	4	4	3	5	3
U02	woman	Ages 31–40	1-2h	Once every 2–3 days	1	4	38	0.64	0.14	0.11	5	5	1	5	3
U03	woman	Ages 31–40	<30min	Once daily	4	5	108	0.48	0.19	0.19	4	3	2	1	2
U04	woman	Ages 25–30	30min-1h	Once daily	5	3	26	0.89	0.40	0.63	4	4	4	5	1
U05	man	18–24 years old	>2h	less than once per week	5	4	114	0.87	0.24	0.68	5	2	2	2	3
U06	man	Ages 25–30	>2h	Once every 2–3 days	4	5	16	0.47	0.28	0.58	1	4	4	2	5
U07	woman	18–24 years old	>2h	Once every 2–3 days	1	4	100	0.79	0.29	0.66	3	4	1	1	5
U08	woman	Ages 31–40	>2h	Several times a day	4	5	76	0.77	0.33	0.32	3	1	1	5	4
U09	woman	Ages 25–30	1-2h	Once every 2–3 days	5	5	95	0.79	0.19	0.22	4	3	1	1	2
U10	woman	Ages 31–40	<30min	Once daily	5	1	23	0.93	0.12	0.52	1	4	4	5	5

Data source: Author-designed questionnaire survey (May 2026)

5. Research Innovations

(1) Theoretical Innovation: Overcoming the limitations of technological centrism and unidirectional research, this study pioneers a bidirectional theoretical framework that systematically integrates algorithmic technology with user behavior, establishing a closed-loop analytical model of "algorithm → user → algorithm"[1,7].

(2) Scenario Innovation: Focusing on the highly time-sensitive and attention-grabbing context of TikTok trending topics, this study fills the gap in refined empirical research on segmented scenarios and single behavioral metrics across a single platform[6].

(3) Methodological Innovation: A hybrid approach combining quantitative core analysis with qualitative supplementation is employed. This methodology not only models and calculates the bidirectional impact intensity but also identifies users' implicit algorithm adoption pathways through interviews, achieving an organic integration of data and theory[2,4].

(4) Innovative Perspective: By integrating both the "algorithm influencing users" and "users taming algorithms" pathways, this approach transforms users from passive recipients of algorithms into active participants, thereby enriching the perspective of subjective agency in human-computer interaction research[5,8,9].

6. Research Conclusions and Practical Recommendations

6.1 Research Conclusion

(1) The TikTok trending algorithm directly influences user engagement duration through three major mechanisms: collaborative filtering, traffic weighting, and real-time feedback loops. The emotional intensity of content, pacing design, and topic popularity collectively affect viewing continuity[3,6,14].

(2) Users are not passive recipients of recommendations; their actions-such as completing episodes, liking content, swiping quickly, showing disinterest, or actively searching-serve as critical signals for algorithmic iteration, enabling the reverse refinement of recommendation logic[5,7,9].

(3) Users with varying levels of algorithmic literacy, different usage durations, and ages

exhibit distinct differences in their engagement patterns and adaptation strategies; those with higher algorithmic literacy are more likely to actively influence recommended content[4,8].

(4) The bidirectional construction mechanism enhances user engagement but may also exacerbate information cocooning and excessive immersion issues. Platforms must strike a balance between efficiency and ethics[11-13,15].

6.2 Practical Recommendations

(1) Platform algorithm optimization: In addition to dwell time and click-through rate, introduce metrics such as content diversity and user subjective satisfaction to reduce reliance on single traffic-driven metrics[1,3].

(2) Trending content management: Dynamically adjust content prioritization based on user feedback signals to increase the exposure ratio of socially valuable and knowledge-based content[6].

(3) Enhanced user experience: Introduce algorithm transparency settings, enable personalized adjustment features, and reduce excessive immersion and echo chamber effects[8,9].

(4) Algorithmic Ethical Governance: Establish an algorithm audit mechanism, standardize the distribution logic of trending topics, and ensure a healthy and sustainable content ecosystem[11-13].

7. Research Gaps and Prospects

The sample size of this study is limited. Future research could expand the scale of questionnaires and interviews to enhance the generalizability of conclusions; further application of panel data and lagged effect models could provide more precise insights into the long-term bidirectional construction process; additionally, cross-platform comparisons of algorithmic differences between platforms such as TikTok and Kuaishou could improve the external validity of the study[2,4,6].

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