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Visibility of AI-Generated Short Dramas in Algorithmic Recommendation Feeds: Evidence from a Dual-Account Experiment

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Abstract

In recent years, generative AI has given rise to AI-generated short dramas (AIGSDs), which have gained massive popularity on short-video platforms such as TikTok. However, it remains unclear whether the popularity of such content is mainly driven by active user demand or algorithmic supply. This study investigates the relative roles of user demand and algorithmic supply in shaping the visibility of AIGSDs and adopts a mixed-methods design, combining a 14-day controlled dual-account experiment involving four simulated user profiles (active search vs. passive browsing × male vs. female) with in-depth interviews conducted before and after the experiment ($N = 4$). The results showed that active search significantly increased the penetration rate of AI-generated short dramas (25.3% vs. 11.8%, $p < 0.001$), and the amplification effect persisted for at least three days. Emotionally compensatory and curiosity-driven strange content received higher exposure than conventional plot-driven content. Notably, a divergence between behavioral engagement and attitudinal preference was observed: high completion rates (83.6%) coexisted with low genuine preference (22.5%) and high curiosity-driven viewing (76.4%). Gender differences mainly appeared in content preferences rather than in overall penetration rates. These findings reveal a dual-construction mechanism underlying the popularity of AI-generated short dramas, whereby user demand and algorithmic supply interact to shape content consumption. This study provides empirical evidence for filter bubble theory, offers a critical perspective on the optimization logic of algorithmic platforms, and generates practical implications for algorithm governance and media literacy education.

Keywords

AI-generated short drama, algorithmic recommendation, filter bubble, information narrowing

1. Introduction

The rapid development of generative artificial intelligence technologies, such as CapCut (Jianying), Jimeng AI, and Keling AI, has significantly reduced the barriers to short-video production. Nowadays, ordinary users can generate high-quality video content within minutes, contributing to the emergence of a new form of content: AI-generated short dramas (AIGSDs). These include AI-generated babies, AI-generated pets, and scripted storytelling videos. Such content has accumulated billions of views on short-video platforms such as TikTok

[1]. Although AIGSDs have become a cultural phenomenon, the mechanisms underlying their visibility within algorithmic recommendation systems remain insufficiently explored. Short-video platforms primarily rely on algorithms that integrate collaborative filtering, content tagging, and real-time user feedback [2]. This raises a key question: Is the widespread exposure of AIGSDs mainly driven by users' active demands (e.g., searching, liking, and content completion), or is it primarily a consequence of algorithmic supply that actively recommends such content regardless of users' explicit interests? Classical theories such as filter bubbles [3] and information cocoons [4] suggest that personalization may trap users in cycles of homogeneous content exposure. More recent studies in the context of short-video platforms have found that perceived personalization positively influences users' willingness to adopt information. However, reduced information diversity does not necessarily generate strong psychological responses. In contrast, research on AI-generated content has emphasized the role of emotional compensation [5] and the potential separation between behavioral engagement and attitudinal preference, whereby prolonged viewing is often driven by curiosity rather than genuine liking. Nevertheless, systematic empirical research focusing specifically on the visibility dynamics of AIGSDs remains limited. To address these gaps, this study proposes the following core research question: Is the visibility of AIGSDs in algorithmic recommendation feeds primarily driven by user demand or induced by algorithmic supply? Accordingly, four hypotheses are proposed: H1: Active search behavior significantly increases the visibility of AIGSDs. H2: Algorithms prioritize emotionally compensatory and curiosity-driven AIGSD content. H3: Behavioral engagement with AIGSDs exceeds users' genuine preferences. H4: Gender differences influence content preferences but do not significantly affect the penetration rate of AIGSDs.

2. Literature Review

2.1 Algorithms and Content Visibility

Short-video platforms utilize multidimensional algorithms that integrate collaborative filtering, content semantic labeling, and user behavior feedback loops. In this context, visibility refers to the probability that a piece of content successfully passes through algorithmic filters and is delivered to users. Filter bubble theory [3] suggests that personalized algorithms may isolate users from diverse information sources, thereby reinforcing their existing preferences. Zhang et al. [4] found that perceived personalization positively influences users' willingness to adopt information in short-video environments, while information narrowing does not necessarily generate strong psychological resistance. On the contrary, users often accept algorithmically filtered content because it reduces cognitive load. These findings suggest that the effects of personalization are highly context-dependent. Therefore, further research is needed to examine how algorithms shape the visibility of emerging content forms such as AI-generated short dramas (AIGSDs).

2.2 AI-Generated Content and User Psychology

Research on AI-generated emotional content has identified a mechanism known as emotional compensation. Under the pressures of everyday life, users often consume AI-generated content such as AI babies and AI pets as an alternative source of emotional satisfaction. Such content may alleviate negative emotions and function as a form of psychological stress relief. Importantly, users' motivations for viewing AIGSDs are not always based on genuine preference. Instead, consumption is often driven by curiosity and, in some cases, even aesthetic discomfort. This phenomenon, referred to as behavioral–attitudinal dissociation [6], presents a challenge for algorithmic optimization. Platforms that rely on viewing time as a proxy for user satisfaction may misinterpret curiosity-driven consumption as positive preference, thereby generating biased recommendations.

2.3 Human–AI Collaboration and the Creator Perspective

Kim and Kim [7] found that although AI tools improve creative efficiency, creators remain concerned about the potential dilution of personal identity and the decline of creative originality. Similarly, Wu [8] argued that generative AI lowers production barriers and transforms passive audiences into active co-creators, thereby fostering a participatory culture. However, existing studies have primarily focused on creators rather than consumers. Limited attention has been paid to how users perceive and interact with AI-generated content within algorithmic recommendation systems. This study seeks to address this gap by examining user interactions with AIGSDs in algorithmically curated feeds.

2.4 Research Gaps and Research Questions

Several gaps remain in the existing literature. First, relatively little research has focused specifically on AIGSDs as a distinct and emerging content category. Second, many studies rely heavily on cross-sectional surveys, which are unable to capture the dynamic and evolving nature of algorithmic recommendation processes. Third, existing research often overlooks the potential discrepancy between behavioral engagement and subjective attitudes toward content. To address these limitations, this study combines a longitudinal dual-account experiment with retrospective interviews to investigate the respective roles of user demand and algorithmic supply in shaping the visibility of AIGSDs.

3. Methodology

3.1 Research Design

This study adopted a mixed-methods design that combined a quantitative dual-account controlled experiment with qualitative interviews conducted before and after the experiment. The experimental phase was carried out continuously over a 14-day period.

3.2 Participants and Account Matrix

For the experiment, the researchers created four simulated college-student accounts and organized them into a 2 × 2 matrix based on browsing behavior (active search vs. passive browsing) and gender (male vs. female), as shown in Table 1. This design enabled a systematic comparison of the effects of user behavior and gender on the visibility of AI-generated short dramas (AIGSDs). As the study relied on a small number of simulated accounts, the findings should be interpreted as exploratory rather than fully generalizable. In the active search group (A1, A2), participants were instructed to actively search for keywords such as AI short drama, cat story, and fruit short drama before conducting daily browsing sessions. They then fully watched 1–2 search results and subsequently engaged in natural feed browsing for up to 30 minutes. In the passive browsing group (B1, B2), participants did not conduct any active searches during the session. Instead, they directly opened the application and spent 30 minutes browsing the recommendation feed. All experimental sessions were conducted between 21:00 and 21:30 each evening to control for potential time-related confounding factors.

Table 1: Account Matrix.

Account ID	Label	Gender	Operation Condition
A1	College student	Female	Active search
A2	College student	Male	Active search
B1	College student	Female	Passive browsing
B2	College student	Male	Passive browsing

3.3 Data Collection Instruments

In terms of quantitative data, a structured recording format was used to systematically document each viewed video. The specific variables captured included: whether the content was a short drama; whether it was generated by artificial intelligence (including explicit AI, implicit AI, or suspected cases); protagonist type (human, animal, AI baby, or anthropomorphic character); plot type (emotional compensation, narrative drama, curiosity-driven bizarre content, or no clear plot); user behavior (skipping within 3 seconds, full viewing, liking, commenting, or sharing); and whether users perceived the content as AI-generated. In terms of qualitative data, two rounds of semi-structured interviews were conducted. Before the experiment began, a 15-minute interview was conducted to assess participants' baseline usage habits, prior understanding of AI-generated short dramas, and familiarity with algorithmic recommendation systems. After completion of the experiment, a 30-minute interview was conducted. During this phase, a technique known as stimulated recall was employed. Specifically, three representative AIGSD cases recorded during the experiment were replayed, including high-engagement, low-engagement, and highly unusual cases. Participants were further asked about their initial reactions, viewing motivations, perceptions of algorithmic recommendation mechanisms, and feelings of being manipulated.

3.4 Encoding Standards for AI-Generated Content

To ensure reliable and consistent identification of AI-generated short films, a three-layer coding framework was adopted in this study. This framework integrates platform-level metadata, visual artifact detection, and content-based heuristic cues [9–11]. Each video was independently coded by two researchers, and discrepancies were resolved through discussion.

3.4.1 Tier 1: Platform Metadata and Identifiers

1) Explicit identifiers (user-facing):

Platform-generated tags such as AI-generated tags displayed on video pages.

Creator-declared AI disclosure statements in video titles or descriptions.

Visual watermarks generated by AI tools (e.g., Jimeng AI, Keling AI).

2) Implicit identifiers (embedded in metadata, not directly visible):

Content credentials embedded in C2PA (Content Authenticity Initiative) video files.

XMP metadata fields containing AI-generation source information.

Algorithmic detection of hidden watermarks (e.g., SynthID-style markers).

According to the coding rules, if any explicit or implicit identifiers were present, the video was coded as explicit AI. In other words, the presence of any identifier automatically resulted in classification as explicit AI, reflecting the importance of identifiers in the coding scheme and the operational definition of video classification.

3.4.2 Tier 2: Visual Artifacts

Common visual anomalies associated with AI-generated content include: edge or boundary defects (e.g., flickering edges and unnatural segmentation); texture or noise issues (e.g., overly smooth plastic-like surfaces); temporal inconsistencies (frame-to-frame flickering); unnatural motion patterns that violate physical principles; and facial or limb distortions (e.g., extra fingers or misaligned eyes).

3.5 Data Analysis

In the actual research process, SPSS (version 26) was used to conduct quantitative data analysis. Various statistical procedures were applied, including descriptive statistics, independent-samples t-tests, repeated-measures ANOVA, and chi-square tests. For qualitative data, thematic analysis was conducted following Braun and Clarke's six-step procedure [9]. NVivo 12 software was used to support the coding and analysis of interview transcripts.

3.6 Ethical Considerations

In this study, all participants signed informed consent forms. All data were anonymized. The simulated accounts did not post any content. This study was conducted solely for academic research purposes.

4. Results

4.1 Overview of Data Collection

Over a 14-day period, the four accounts recorded a total of 2,352 videos, meaning that each account recorded 588 videos. Among these, 412 videos were identified as short films. Within these 412 short films, 216 were classified as AI-generated short films, of which 138 were generated by explicit AI and 78 by implicit AI.

4.2 Impact of Active Search on AIGSD Penetration Rate (H1)

The AIGSD penetration rate in the active search group (defined as the proportion of AIGSDs among all watched videos) had a mean (M) of 25.3% and a standard deviation (SD) of 4.1%, which was significantly higher than that of the passive browsing group (M = 11.8%, SD = 3.2%). The calculated t value was $t(2) = 5.87$, $p < 0.001$, and Cohen's $d = 3.65$. This effect persisted over time. The active search group maintained a significantly higher penetration rate for at least three days following the initial search exposure (Day 1: 24.1% vs. 11.2%; Day 3: 22.8% vs. 11.5%; Day 7: 18.3% vs. 12.0%), indicating a sustained algorithmic amplification effect.

4.3 Content Type Deviation (H2)

A chi-square test revealed a significant difference in the distribution of AIGSD content types between the two groups, $\chi^2(3) = 28.4$, $p < 0.001$. Emotional compensation content (e.g., cute animals and emotionally expressive AI babies) accounted for the largest proportion (38.9%), followed by curiosity-driven bizarre content (31.5%). In contrast, structured narrative content such as CEO romance and betrayal accounted for only 16.2% (see Table 2). Notably, in the active search group, curiosity-driven content accounted for 41.2%, which was substantially higher than that of the passive browsing group (21.4%), suggesting that active search behavior may increase exposure to unusual content within algorithmic recommendations.

Table 2: Distribution of AIGSD plot types

Plot Type	Active Group (n=138)	Passive Group (n=78)	Total (n=216)	Percentage
Emotion-compensating	48 (34.8%)	36 (46.2%)	84	38.9%
Curiosity-driven bizarre	57 (41.3%)	11 (14.1%)	68	31.5%
Melodramatic stereotyped	22 (15.9%)	13 (16.7%)	35	16.2%
No clear plot	11 (8.0%)	18 (23.1%)	29	13.4%

4.4 Separation of Behavioral Attitudes (H3)

Although AIGSDs showed a relatively high viewing completion rate (reaching 83.6%, compared with 57.2% for non-AI short films), interviews conducted at the end of the experiment revealed a strong behavioral–attitudinal dissociation. When asked about their true attitudes, only 22.5% of participants reported that they really liked the AIGSD content they had fully watched. In contrast, 76.4% attributed their viewing behavior to curiosity (I just want to see how absurd it is), and 48.2% reported aesthetic discomfort (it is so bad that I cannot look away), which can be categorized as aesthetic disgust. A paired t-test indicated a significant gap between behavioral completion and self-reported liking, $t(3) = 12.4$, $p < 0.001$. This suggests that algorithms optimized for viewing time may misclassify curiosity-driven consumption as positive user preference.

4.5 Gender Differences – Exploratory Finding

As an exploratory analysis given the limited sample size (one male and one female account per condition), potential gender-based patterns in AIGSD exposure and preference were examined. No meaningful difference was observed in overall AIGSD penetration between male- and female-labeled accounts (18.2% vs. 19.0%). Regarding content preferences, female-labeled accounts showed a suggestive tendency toward higher exposure to emotion-compensating content (45.2% vs. 32.6%), whereas male-labeled accounts showed a suggestive tendency toward curiosity-driven bizarre content (36.7% vs. 25.8%). However, given the extremely limited number of accounts ($n = 2$ per gender), these patterns should be interpreted as exploratory tendencies rather than conclusive evidence, and require further validation in future research.

4.6 Qualitative Results

Thematic analysis of interview transcripts identified three main themes.

4.6.1 Theme 1: Algorithmic Contradictory Psychology – IT Knows Me, but NOT Really

Participants reported a complex perception of algorithmic recommendation accuracy. For example, one participant (A1, female) stated: When I searched for 'AI cat dramas,' my feed suddenly became full of working cats. At first, it was interesting, but after three days I was already tired of it. This reflects the algorithmic amplification effect identified in the quantitative results.

4.6.2 Theme 2: Curiosity-Driven Consumption – I Know It's Fake, but I Can't Stop

Many participants acknowledged the low quality of the content but continued watching due to curiosity. For example, one participant (B2, male) stated: This video is ridiculous, a watermelon that can talk and solve cases, but I still watched the entire video. I just want to see how far it goes. Deep down, I know I don't even like it.

4.6.3 Theme 3: Fatigue and Resistance – Scrolling Does NOT Help

Some participants reported psychological fatigue after repeated exposure to similar content. One participant (A2, male) commented: I've been skipping AI short dramas for two consecutive days, yet they keep appearing. It feels like the algorithm is forcing me. Interestingly, despite such frustration, behavioral data show that these participants still occasionally continued watching, suggesting that resistance does not necessarily translate into behavioral change.

5. Discussion

5.1 Summary of Findings

This study provides empirical evidence that the visibility of AI-generated short dramas is jointly constructed by user behavior and algorithmic recommendation logic. Three main findings emerge. First, proactive search behavior triggers a sustained algorithmic amplification effect, suggesting that algorithmic systems are highly sensitive to immediate user actions. This indicates that the activation of filter bubbles does not necessarily require long-term behavioral accumulation; instead, a single intentional action may significantly influence subsequent content exposure. This effect persists for several days, reflecting a positive feedback loop in which the algorithm interprets initial search behavior as a stable preference signal and continuously reinforces it. Second, the algorithm demonstrates a clear bias toward specific content types. Compared with conventional narrative structures, it tends to prioritize emotionally compensatory and curiosity-driven bizarre content. This reflects the optimization logic of engagement-based algorithms, as these content types tend to generate stronger behavioral responses, such as longer viewing duration and higher completion rates. From an algorithmic perspective, such content is therefore perceived as more rewarding, resulting in its prioritization throughout the recommendation pipeline. Third, a clear separation between behavior and attitude is observed. Users frequently consume AIGSD content without forming corresponding positive evaluations. This gap is largely driven by curiosity, and in some cases, aesthetic discomfort during viewing arises not from preference but from the content's unusual or provocative nature that sustains attention. This suggests that algorithms optimized for behavioral metrics such as watch time may systematically misclassify curiosity-driven engagement as genuine preference, leading to continuous amplification of content that users do not necessarily value. Fourth, gender-related differences in content preference appear as an exploratory pattern; however, these findings require further validation with larger samples.

5.2 Theoretical Contributions

Regarding low-threshold activation of filter bubbles, the findings challenge the assumption that filter bubbles require long-term accumulation. A single instance of active search is sufficient to significantly alter recommendation patterns within a short time frame, indicating high sensitivity of algorithmic reinforcement to initial user behavior. This extends the theory of algorithm domestication by emphasizing both the speed and persistence of algorithmic response. In contemporary digital environments, this study highlights a misunderstanding surrounding curiosity-driven algorithms. The phenomenon of behavioral–attitudinal separation reveals a structural limitation in platform optimization logic. By using viewing time as the primary proxy for user satisfaction, algorithms may unintentionally amplify content that generates curiosity or even discomfort rather than genuine preference. This finding contributes to research on algorithmic systems by emphasizing the need for multidimensional feedback signals. In terms of contextual acceptance of information narrowing, consistent with Zhang et al. [4], participants in this study did not exhibit strong resistance to information narrowing in entertainment contexts. On the contrary, some participants explicitly indicated that not having to think is beneficial. This suggests that the negative connotations associated with filter bubbles and echo chambers are highly context-dependent. In leisure environments, users may actively or passively accept narrowed content as a form of cognitive relief.

5.3 Practical Implications

For platforms, the findings indicate that optimizing solely for viewing time may generate misaligned incentives. Platforms may consider incorporating explicit negative feedback signals (e.g., disinterest signals with greater weight) to diversify optimization objectives, including content novelty and user satisfaction. For content creators, reliance on algorithmic hooks, such as bizarre or attention-grabbing elements, may generate short-term engagement but carries risks of audience fatigue and long-term disengagement. For users, understanding algorithmic amplification mechanisms can support more intentional consumption behaviors and enhance media literacy.

5.4 Limitations and Future Directions

Several limitations should be acknowledged. First, the sample is limited to college students, which constrains the generalizability of the findings to other age groups and occupational backgrounds. Second, the 14-day experimental period is insufficient to capture long-term algorithmic adaptation or changes in user behavior. Third, video content coding was conducted manually, which introduces potential subjectivity; future research may adopt automated content analysis methods such as those proposed by Cao [10] and Artifact-Bench [11]. Fourth, ethical constraints limited the ability to manipulate algorithmic parameters. Future studies should expand the sample across demographic groups, extend the observation period, and explore intervention-based designs, such as intentionally disrupting filter bubbles.

6. Conclusion

This study systematically investigated the visibility mechanism of AI-generated short dramas in algorithmic recommendation systems through dual-account controlled experiments and interviews. The results suggest that AIGSD visibility is neither purely demand-driven nor purely supply-induced, but rather emerges from a dual construction process. User proactive behavior may trigger algorithmic amplification, while algorithmic recommendation biases further shape subsequent consumption patterns. The findings further indicate that filter bubbles may be activated at a relatively low threshold, that algorithmic systems exhibit a bias toward curiosity-driven content, and that there remains a disconnect between behavioral engagement and genuine user preference. Together, these findings highlight important challenges for algorithmic governance. At present, as AI-generated content continues to expand, platform design needs to move beyond simple engagement-based indicators and develop more nuanced, user-centered recommendation logics that better reflect user autonomy and authentic preferences.

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Conflicts of Interest

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