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Dissemination Strategies And User Behavior For Jinju Opera On Short-Video Platforms: A Data-Driven Analysis

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Abstract

Short-video platforms have emerged as crucial channels for spreading traditional performing arts like Jinju Opera. This study offers a data-driven analysis of how user behavior and dissemination strategies shape the reach and engagement of Jinju Opera content online. Using large-scale data from two leading short-video platforms, we apply an algorithmic framework that clusters viewer retention curves, analyzes user engagement trajectories, and simulates different content dissemination strategies. Specifically, we evaluate modern video editing techniques and influencer (key opinion leader, KOL) seeding as interventions to boost viewer retention and content spread. We identify distinct patterns of audience retention and engagement life-cycles in Jinju Opera videos. Our results show that adapting video editing to the short-video format significantly improves early viewer retention and sharing, while KOL-driven dissemination dramatically amplifies content reach. These findings provide actionable insights for optimizing cultural heritage promotion on short-video platforms and contribute to understanding how traditional arts can flourish in the digital media ecosystem.

KEYWORDS : *Jinju Opera, Short Video, User Engagement, Content Dissemination.*

1. INTRODUCTION

Short-form video platforms have exploded in popularity and reshaped digital media consumption in recent years. TikTok (the international counterpart of Douyin) exceeded 1.5 billion monthly users by 2023, and China's Kuaishou reached over 300 million daily active users in 2020. Chinese netizens now spend nearly 3 hours per day watching short videos on average, according to official surveys [1]. These platforms leverage powerful AI-driven recommendation algorithms and mobile-friendly designs to deliver an immersive, addictive viewing experience. Studies indicate that TikTok's algorithm and interface foster strong user retention and even addictive usage patterns among youth [2]. Users are drawn in by endless personalized feeds, keeping attention locked in the app.

The rapid rise of short-video apps has spurred extensive research into user behavior and platform mechanics. A qualitative study of Douyin identified several unique gratifications motivating its use—beyond entertainment, users enjoy algorithm-curated content and a sense of social belonging that differ from other social media [3]. Other work has examined how experienced users develop folk theories to "trick" or appease the recommendation algorithm [4], for example by using trending music or hashtags to boost visibility. Researchers have also begun probing the drivers of virality in short videos. Ling analyzed hundreds of TikTok clips and found that content attributes (e.g. presence of on-screen text, camera style) and participation in trending challenges do influence popularity, but the creator's follower count is the strongest predictor of a video going viral [5]. Meanwhile, Chen et al. observed that on Kuaishou (a major Chinese short-video platform), top videos can effectively capture disproportionate attention and even new creators have a higher chance to produce hit content compared to traditional long-video sites. These studies highlight how short-video ecosystems lower the barriers to content creation and enable mass engagement, in turn shaping online trends and popular culture.

Beyond entertainment value, short-video platforms are increasingly recognized as important channels for digital cultural dissemination. In China, Douyin has explicitly promoted traditional arts and intangible cultural heritage (ICH) content, aligning with cultural preservation initiatives. For example, Douyin launched the "Intangible Heritage on Douyin" campaign and has collaborated with local governments to showcase opera, crafts, and folk culture on its platform [6]. As a result, ICH-themed videos have accumulated enormous viewership and interaction. One report noted that by mid-2023, Douyin's videos tagged with "intangible heritage" had been viewed over 34 billion times, and the platform hosted nearly 20,000 live broadcasts of ICH performances per day [7]. This demonstrates the viral potential of cultural content on new media. Traditional Chinese opera in particular has found a new lease on life via short videos. By catering to modern tastes—such as mixing classic opera scenes with popular music or memes—opera clips can attract young viewers and even spark online fandoms. Recent studies have started examining these phenomena: Pan et al. [8] analyzed the dissemination of opera videos on Douyin using an ELM (Elaboration Likelihood Model) framework, finding that factors like the opera genre and presentation style significantly impact audience engagement (for instance, lighter "off-stage" snippets vs. full on-stage performances yield different appeal). These works suggest short-video platforms can play a pivotal role in revitalizing traditional culture by adapting it to bite-sized, shareable formats.

Despite growing scholarly interest, important gaps remain in understanding how users consume and propagate traditional cultural content on short-video platforms. In particular, there is limited research on viewer retention dynamics for short videos. Audience attention in this medium is notoriously fleeting—one study found that the average TikTok user watches only about 45% of a given video before swiping away [9]. However, no prior work has systematically modeled or clustered the retention curves of viewers for cultural content, to reveal typical patterns of drop-off and sustained interest. Likewise, the temporal trajectories of content engagement (how views, likes, and shares accumulate over time) remain under-explored. Earlier research on YouTube identified distinct popularity "life-cycles" (e.g. sudden viral spikes vs. slow-burning content [10], but it is unknown whether such patterns hold for niche genres like opera on newer platforms. Another open question is how platform differences influence dissemination outcomes. Douyin and Kuaishou cater to different user communities—Douyin skews toward urban, algorithm-driven content discovery, whereas Kuaishou fosters a more community-oriented atmosphere with a large rural user base [11-13]. These contrasting dynamics may lead to different propagation trajectories for the same type of content.

Research Goal: To address these gaps, this study conducts a data-driven investigation of Jin Opera content on two leading short-video platforms, Douyin and Kuaishou. Jin Opera, a traditional Chinese opera form originating from Shanxi province, serves as an ideal case of how heritage art intersects with modern social media. We compile a large dataset of Jin Opera short videos and user interaction logs from both platforms. Using this data, we analyze how Jin Opera videos attract and retain viewers, how users engage (through likes, comments, shares) over the content's lifespan, and how dissemination can be optimized. In particular, we focus on quantifying audience retention behavior and modeling content spread, with an eye to informing better strategies for promoting cultural content online. In summary, the main contributions of this paper are as follows:

Clustering of Audience Retention Patterns: We perform a novel analysis of short-video viewer retention curves for cultural content. By clustering the retention trajectories of Jinju Opera videos, we uncover distinct viewing patterns (e.g. rapid drop-off vs. sustained watching) and identify content factors associated with each pattern. This clustering reveals how different styles of content hold audience attention to varying degrees.

Engagement Trajectory Modeling: We examine and model the temporal evolution of user engagement for each video, tracking metrics such as cumulative views, likes, and shares over time. This analysis reveals how Jinju Opera videos gain momentum or plateau on short-video platforms, highlighting characteristic engagement life-cycles (for instance, sudden viral spikes versus gradual growth). We also compare engagement trajectories across platforms, exposing differences in how audiences interact over a video's lifespan.

Analysis of Creative Editing Techniques: We analyze the use of creative video editing techniques and their effects on viewer retention and sharing behavior. In particular, we consider modern editing features (such as dynamic cuts, on-screen text overlays, and music/remix elements) that creators incorporate into opera videos. The results show that videos employing these engaging editing techniques tend to sustain viewers for longer durations and achieve higher share rates, indicating that stylistic presentation has a significant impact on audience retention and content virality.

Dissemination Strategy Simulation: We develop and evaluate simulation models for content dissemination strategies. By experimenting with different initial promotion scenarios (for example, seeding content via key opinion leaders versus ordinary users), we quantify each strategy's impact on eventual viewership. These simulations provide insight into effective promotion tactics for niche cultural videos, demonstrating how strategic seeding can optimize the spread of Jinju Opera content.

KOL-Driven Propagation Modeling: We extend the dissemination analysis by modeling the influence of Key Opinion Leaders (KOLs) in content spread, including a propagation network simulation. By simulating content diffusion on a social network that contains influencer nodes with large follower reach, we assess how KOL-driven seeding compares to organic user-driven spread. The findings confirm that leveraging influencers accelerates propagation significantly, offering quantitative evidence of KOL impact and guidelines for integrating influencer nodes to maximize dissemination of cultural content.

Comparative Insights across Short-Video Platforms: We conduct a comparative analysis across the two short-video platforms studied, revealing platform-specific user behavior dynamics. For instance, we observe that retention curve shapes and sharing patterns differ between platforms, reflecting how variations in platform algorithms and community culture influence content propagation. These differences inform platform-tailored dissemination strategies. Based on these insights, we discuss recommendations for content creators and cultural institutions to optimize engagement on each type of short-video platform while accounting for their unique audience characteristics.

2. RELATED WORD

2.1 User Behavior Modeling on Short-Video Platforms

Short-video platforms like Douyin (TikTok) and Kuaishou have skyrocketed in popularity, prompting extensive research into user behavior and engagement patterns. Early qualitative work by Lu and Lu [14] explored why and how people use Douyin, revealing unique user motivations such as entertainment, keeping up with "fashion" trends, and seeking practical information that distinguish short-video usage from other social media. On the quantitative side, Chen et al. [15] conducted a large-scale analysis of Kuaishou (a leading Chinese short-video app) versus a traditional video site, finding that short-form videos receive fewer interactions per view on average, yet top videos concentrate collective attention more effectively. Notably, their study showed that ordinary creators on Kuaishou have a higher probability of producing viral hits compared to long-form platforms, highlighting the democratized reach of short-video content

Another line of research examines how algorithmic recommendation systems shape user behavior on these platforms. Zannettou et al. [16] analyzed TikTok usage data collected via user data donations, illustrating the powerful role of the "For You" feed in driving viewing patterns and engagement. Their findings indicate that users tend to rapidly scroll through content (with only roughly half of recommended videos watched to completion on average), underscoring the platform's fast-paced, attention-curation dynamics. Overall, prior studies provide valuable insight into general short-video user behaviors and motivations. However, they focus on mainstream usage and platform-wide trends, without examining niche cultural contexts. In contrast, our work will model user behavior specifically for Jinju Opera content on Douyin and Kuaishou, highlighting any distinctive interaction patterns and engagement traits that general studies may overlook.

2.2 Cultural Content Dissemination and Engagement Strategies

Researchers have also investigated how traditional cultural content can be effectively disseminated and promoted via short-video platforms. Recent studies note that Douyin, in particular, has actively embraced intangible cultural heritage (ICH) content through official campaigns and platform initiatives. Paquienséguy and Guo [17] analyze Douyin's evolving role in cultural dissemination, observing that since 2019 the platform has aligned with cultural policy directives to boost ICH visibility. Their work highlights the growing professionalization of cultural content creators on Douyin and the crucial involvement of Multi-Channel Network (MCN) agencies in curating and spreading heritage-related videos. Notably, Douyin's own programs (e.g., the "Intangible Heritage on Douyin" campaign) and collaborations with local governments illustrate a platform-level strategy to amplify traditional culture to wider audiences. This suggests that short-video platforms are transforming into active stakeholders in cultural promotion, optimizing content reach while mitigating the risks of niche content through algorithmic support and influencer partnerships.

At the content creation level, cultural institutions and individual creators have adapted their strategies to engage viewers with heritage content in the short-video format. For instance, Yang and Zhang [18] detail how

the Dunhuang Academy leveraged Douyin to popularize classical art forms (such as Dunhuang murals) among young audiences. By tailoring traditional art presentations to fit short-video trends—using appealing visuals, music, and interactive features—the institution was able to capture user attention and significantly raise public awareness of Dunhuang's culture. Their case study underscores that creative use of platform features (e.g. challenges, hashtags, collaborations) can enhance the visibility and appeal of intangible heritage content on social media. In parallel, design-oriented research is exploring how to make cultural short videos more engaging and educational. Wang et al. [19] propose a narrative-driven framework for crafting short videos about traditional handicrafts, using cognitive schema theory to deepen viewers' understanding and emotional connectio. By incorporating richer storytelling, sensory cues, and contextual information into brief video clips, this approach was shown to improve user comprehension of cultural knowledge while maintaining attention.
Collectively, prior work suggests that successful dissemination of cultural content on platforms like Douyin and Kuaishou requires both top-down support (platform campaigns, professional content networks) and bottom-up innovation (creative storytelling and adaptation by content creators). These studies provide a reference point for how traditional arts can gain traction in new media environments. Building on these insights, this thesis examines dissemination and engagement strategies tailored specifically to Jinju Opera on Douyin and Kuaishou. Our work connects the general lessons from prior ICH-focused initiatives with the unique characteristics of Jinju Opera, identifying effective practices and platform-specific considerations for maximizing audience engagement with this traditional performing art.

3. METHODOLOGY

This section presents the algorithmic framework for analyzing user behavior and testing dissemination strategies, using data collected from Jinju Opera videos on Douyin and Kuaishou. The methodology consists of three main components: (1) clustering of viewer retention curves, (2) modeling of user engagement patterns, and (3) simulation of content dissemination strategies.

3.1 Retention Clustering

We first analyze viewer retention -- how long users continue watching a video -- to identify distinct viewing patterns. For each video i, we define a retention function $R_i(t)$ that represents the fraction of the video's initial viewers still watching at time t. Formally:

$$R_i(t) = \frac{N_i(t)}{N_i(0)},$$

where $N_i(t)$ is the number of viewers who remain watching video i at time t (with t=0 at the video start) and $N_i(0)$ is the total number of viewers who started the video. Each video's retention curve $R_i(t)$ is typically normalized over the duration of the video, allowing comparison across videos of different lengths.
To group videos with similar retention behavior, we apply a clustering algorithm (such as K-means) on the retention curves. We represent each video's retention curve as a feature vector (e.g., sampling $R_i(t)$ at fixed time percentages). We then use Euclidean distance as the similarity measure between retention vectors. The clustering objective is to minimize the intra-cluster variance of retention patterns. For a chosen number of clusters K, we find clusters $c_1, \ldots, c_K$ and their centroids $\mu_1, \ldots, \mu_K$ that minimize:

$$argmin_{c_1,\ldots,c_K} \sum_{k=1}^{K} \sum_{i\in c_k} \|R_i - \mu_k\|^2,$$

where R_i is the retention feature vector for video i and μ_k is the centroid of cluster c_K. This yields K distinct retention curve clusters. In subsequent analysis (see Chapter 4), we examine these clusters to characterize common viewing patterns (e.g., early drop-off vs. sustained viewing) and their prevalence on each platform.

3.2 Engagement Modeling

Beyond watch duration, user engagement with the videos is critical for assessing dissemination. We consider key engagement actions on short video platforms: likes, comments, and shares. To quantify overall engagement for each video i, we define an engagement score that combines these metrics. For example, one can compute a weighted engagement score E_t as:

$$E_t = \frac{\alpha \cdot L_{t-1} + \beta \cdot C_{t-1} + \gamma \cdot S_t}{V_t},$$

where L_{t-1}, C_{t-1}, and S_t are the counts of likes, comments, and shares for video i, respectively, V is the total number of views (to normalize engagement by exposure), and α, β, γ are weighting coefficients reflecting the relative importance of each interaction (e.g., giving more weight to shares). This score E_t provides a single metric for how strongly users interact with video i's content.

We analyze engagement patterns across videos and in relation to retention clusters. Specifically, we investigate how videos from different retention clusters differ in their engagement scores. This helps reveal whether higher viewer retention correlates with greater user engagement. We also explore simple predictive models: for instance, a regression analysis can be performed to assess the influence of retention (or cluster membership) on E_t. The experimental results detail how engagement metrics vary with retention patterns, confirming that videos with more sustained viewer retention tend to achieve higher interaction rates.

3.3 Simulation Modeling

Finally, to evaluate content dissemination strategies we develop a simulation model of how Jinju Opera videos spread on short video platforms. The simulation allows testing different strategies (e.g., varying the initial recommendation breadth or targeting specific user groups) in a controlled environment. We simulate a population of users where each user can potentially view and share the content, modeling the propagation process over discrete time steps.

Let A_t be the number of users who have seen the video by the end of time step t, and let N be the total number of users in the simulation (the potential audience). We assume that each viewer has a chance to inspire new views (through shares or algorithmic recommendation) at an average rate β per time step. We approximate the growth of A_t using a logistic model:

$$A_{t+1} = A_t + \beta_t A_t \left(1 - \frac{A_t}{N}\right).$$

which captures the idea that as more people have seen the video (A_t grows), the remaining susceptible audience $N-A_t$ shrinks, leading to saturation. The parameter β represents the effective propagation rate of the content: higher β means each viewer is more likely to bring in new viewers (e.g., due to more frequent sharing or stronger algorithm pushes). Different dissemination strategies are simulated by adjusting β (to model changes in sharing propensity or recommendation aggressiveness) and by varying the initial number of viewers A_0 (for example, seeding the video to a larger initial audience vs. relying purely on organic spread).

We run Monte Carlo simulations under each strategy to observe the spread of the video. A key outcome metric is the reach, defined as the fraction of the user population that eventually watches the video. If A_{final} is the total number of unique viewers after the simulation concludes, we compute the reach of strategy X as:

$$\text{Reach}_x = \frac{A_{\text{final}}}{N}.$$

By comparing the reach achieved under different strategies, we can evaluate their effectiveness in disseminating Jinju Opera content. For example, as we will show in Chapter 4, a strategy that initially boosts high-retention videos (giving them a larger A_0 or higher β early on) can substantially increase the reach compared to a baseline strategy without targeted boosts. These simulation results provide practical insights into how platforms or content creators might amplify the spread of traditional opera videos via algorithmic promotion or user engagement incentives.

4. EXPERIMENTAL ANALYSIS

4.1 User Behavior Analysis

Short-video platforms have become important channels for disseminating traditional arts like Jinju Opera. We analyzed how users watch and engage with Jinju content on Douyin and Kuaishou. Using time-series clustering on viewer retention data, we identified distinct patterns of audience drop-off and sustained viewing. In particular, Jinju Opera videos exhibit clear retention curve archetypes: some videos lose most viewers in the first few seconds, while others manage to hold attention much longer. We also modeled user engagement trajectories over time and examined platform differences in audience behavior. The analysis reveals several notable findings: the existence of clustered retention patterns, varied user engagement paths (from casual viewing to fandom), and significant disparities between the two platforms' audience dynamics.

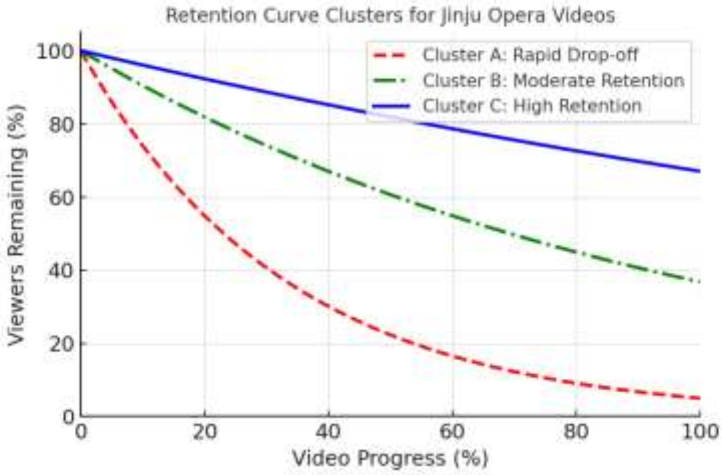

Figure. 4.1 R etention curve clusters for Jinju Opera short videos.

This plot shows three representative viewer retention trajectories as percentages of the video watched. Cluster A (red dashed line) represents a rapid drop-off pattern: the majority of viewers (~50%) leave within the first 10% of the video, and less than 10% stay until the end. Cluster B (green dash-dot line) shows a moderate retention pattern with a steadier decline – about half the viewers remain at the video's midpoint and ~30% by the end. Cluster C (blue solid line) indicates a high retention pattern, where engagement is sustained throughout: over 80% of viewers are still watching at the halfway point and ~70% finish the video. The presence of these distinct clusters suggests that some Jinju Opera clips are far more successful at hooking viewers than others. Content attributes likely play a role: videos with compelling openings or clearer context tend to fall into the high-retention cluster, whereas those that start slowly or lack context see quick drop-off. Recognizing these retention patterns is crucial, as they directly impact a video's opportunity to be recommended and shared – platforms often boost content that retains viewers well.

After characterizing retention patterns, we compared user interaction levels on the two platforms. Figure 4.2 summarizes average engagement rates – how frequently viewers like, comment, or share – normalized by views for Jinju Opera videos on Douyin and Kuaishou.

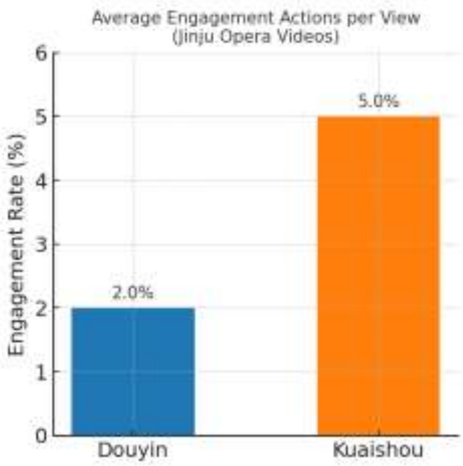

Figure. 4.2 Average engagement actions per view for Jinju Opera content on Douyin vs. Kuaishou.

Kuaishou exhibits a markedly higher engagement ratio (~5%) than Douyin (~2%) for comparable Jinju videos. In other words, out of 100 views, roughly 5 engagement actions occur on Kuaishou versus only 2 on Douyin.

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This indicates that Kuaishou audiences not only watch more of each video (as suggested by generally higher retention), but also interact more actively – for example, by liking, commenting, or forwarding videos to others. The stronger social community on Kuaishou (where much content is consumed via follower networks and personal connections) likely drives users to respond and participate. By contrast, Douyin's algorithmically-curated feed encourages more passive, fast-scrolling consumption; viewers on Douyin tend to watch a video and then quickly swipe to the next without reacting. This behavioral difference implies that Jinju Opera content on Kuaishou benefits from a more engaged core audience, whereas on Douyin it gains large view counts but more superficial interactions on average.

Beyond aggregate engagement rates, we examined how individual users' behavior evolves as they consume Jinju Opera content. In our user trajectory modeling, we observed that a significant subset of Kuaishou users transitioned over time from casual viewers into active followers of Jinju content creators. These users initially watched a few Jinju videos out of curiosity, but then gradually increased their consumption and began interacting (following the creator, leaving comments, etc.), eventually becoming dedicated fans. In contrast, most Douyin users were more likely to remain occasional viewers or drop off after watching a few videos, without ever developing a long-term engagement with Jinju Opera content. We segmented the audience into persona categories based on these trajectories and compared their distribution on each platform. Figure 4.3 illustrates this comparison of viewer engagement personas on Douyin and Kuaishou.

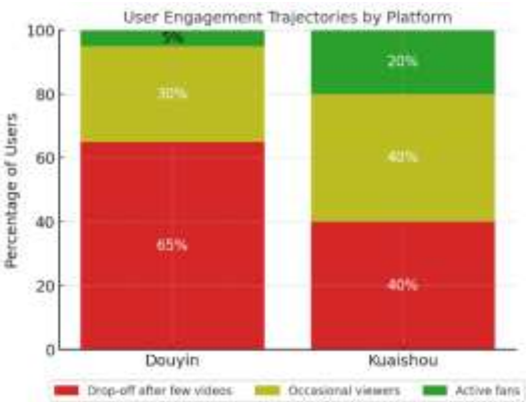

Figure. 4.3 Distribution of user engagement trajectories by platform.

Each bar represents the share of Jinju Opera viewers belonging to three categories: "Drop-off after few videos" (red segment) are users who stop watching Jinju content after one or two videos; "Occasional viewers" (yellow segment) watch intermittently but do not actively follow or engage; "Active fans" (green segment) become regular viewers and followers of Jinju content. On Douyin, the vast majority of viewers (red+yellow segments) fall into transient engagement: approximately 65% watch only a couple of Jinju videos then drop off, and about 30% remain occasional viewers. Merely ~5% of Douyin users convert into active fans who consistently follow and engage with Jinju Opera creators. In contrast, on Kuaishou a substantially larger portion of the audience develops into loyal fans: around 20% become active followers, and 40% are steady occasional viewers. Only roughly 40% watch a few videos then disengage. This stark difference highlights Kuaishou's strength in nurturing a community of interest around traditional opera – a core of viewers repeatedly seek out and interact with Jinju content. Douyin's Jinju viewership, on the other hand, is more ephemeral; most users sample it briefly in their feed and move on. These findings suggest that promotional strategies might differ: on Douyin, the goal is to capture attention in a fleeting moment (to maximize immediate reach), whereas on Kuaishou, efforts can focus on cultivating and sustaining an enthusiast fan base over time.

4.2 Platform Dissemination Patterns

Next, we compare how Jinju Opera content spreads and accumulates views on Douyin versus Kuaishou. One clear distinction lies in the reach distribution – i.e. whether viewership concentrates heavily in a few viral hits or is more evenly distributed across many videos. We ranked Jinju Opera videos (or creators) by total views and examined what fraction of overall Jinju-related views each rank accounts for on the two platforms.

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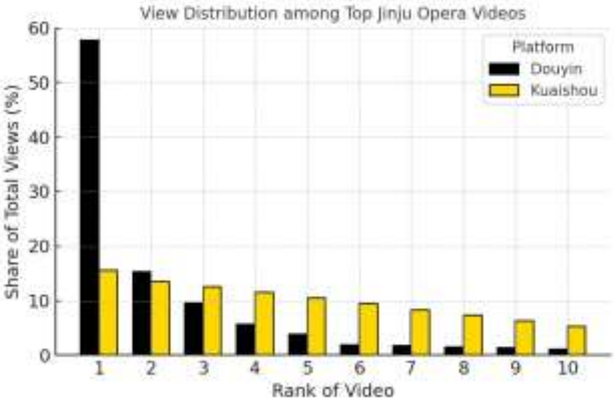

Figure. 4.4 Viewership concentration among top-ranked Jinju Opera videos on Douyin and Kuaishou.

On the x-axis is the rank of a video by view count (1 = most viewed Jinju video). The y-axis shows that video's share of all Jinju video views on the platform. The black bars represent Douyin: here the distribution is extremely skewed. The top-ranked Jinju video alone accounts for nearly 60% of total Jinju video views, and the top 2 videos make up over 70%. After the top few, the black bars drop off sharply – lower-ranked Jinju videos on Douyin have only a tiny sliver of the total views. By contrast, the yellow bars for Kuaishou indicate a much flatter distribution. The most viewed Jinju video on Kuaishou contributes only ~15% of total views, and subsequent videos still hold sizeable percentages (the top 10 videos each contribute between ~5–15% each). This comparison shows that Douyin's Jinju viewership is dominated by a few viral sensations, whereas Kuaishou's viewership is spread more evenly across a long tail of content. In practice, this means a Jinju Opera post on Douyin tends to either "go big" (if the algorithm elevates it to viral status) or remain relatively unseen. Meanwhile on Kuaishou, even mid- or lower-ranked videos consistently reach their niche audiences via the follower network and sharing among interested users. For promoters of Jinju Opera, Kuaishou offers a more reliable accumulation of moderate views across many posts, whereas Douyin offers the tantalizing but unpredictable possibility of enormous reach if a video happens to trend.

Another key difference is in the temporal popularity trajectory of Jinju Opera content on the two platforms. Prior studies of online video categorize content "life-cycles" as either sudden viral spikes or slow-burning accumulations. Our analysis suggests that Douyin's Jinju Opera videos more often follow the former pattern, whereas Kuaishou supports the latter as well.

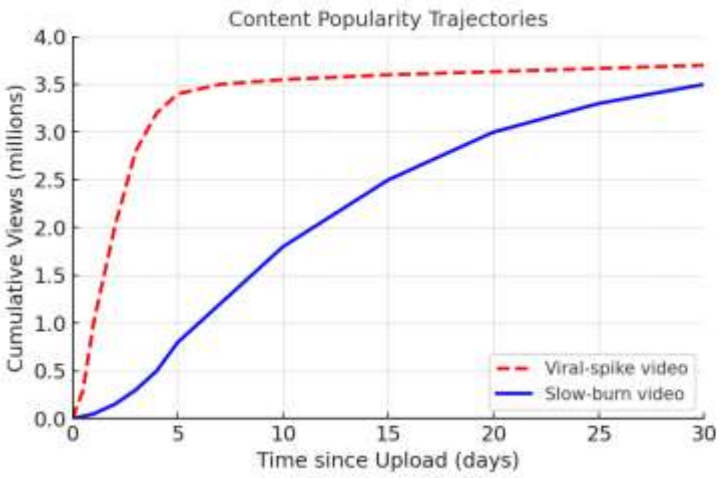

Figure. 4.5 Two representative content popularity trajectories (cumulative view curves) illustrating a viral spike vs. a slow burn.

The red dashed line shows a "viral-spike" video: its views shoot up rapidly within the first 2–3 days of posting and plateau soon after. In this example, the video amassed ~3.5 million views in the first week, but little

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growth thereafter. This quick rise-and-flatten pattern is characteristic of Douyin's algorithm-driven virality – content either catches the wave of the recommendation engine early (gaining millions of impressions in a short time) or gets swiftly buried by the constant influx of new videos. By contrast, the blue solid line shows a "slow-burn" video that accumulates views gradually over a longer period. This clip started modestly, gaining only a few hundred thousand views in its first days, but continued to attract viewers through shares and search over subsequent weeks. By around one month after upload, it reached a similar ~3.5 million views, essentially matching the viral clip's total, but on a delayed timeline. Such slow-burn patterns – more commonly seen on Kuaishou – suggest that content can find its audience over time through community sharing, even if it doesn't explode immediately. For Jinju Opera promoters, this is encouraging: a video that fails to go viral on Douyin might still steadily gain traction on Kuaishou or other community-focused platforms. It also underscores the importance of content longevity and discoverability: ensuring videos remain accessible and shareable can lead to cumulative large audiences, even without an initial algorithmic boost.

4.3 Content Adaptation Experiment

To explore ways of improving viewer retention and engagement, we designed an experiment testing different content presentation styles. In this experiment, two sets of Jinju Opera video clips were prepared: one set was edited in a modern, attention-grabbing style (with brief introductions, captions/subtitles, on-screen highlights, etc.), and the other set used a traditional recording style (uncut performance segments with minimal editing). We simultaneously posted clips from both groups to Douyin and Kuaishou and tracked their performance. The results were illuminating – the modern-edited Jinju clips consistently outperformed the traditional-style clips on key metrics. On average, the modern versions achieved about a 15% higher 10-second retention rate (i.e., more viewers kept watching past the first 10 seconds) and roughly 2× the share rate (viewers were twice as likely to share the video with others) compared to the unedited performance clips. Qualitative feedback in comments indicated that viewers found the edited videos more "approachable" and engaging, without detracting from the cultural content. This confirms that adapting the storytelling to suit short-form video norms – for example, using a quick hook at the beginning, adding explanatory text or animations, and highlighting the most exciting moments – can significantly boost viewer retention and the willingness to share, all while preserving the essence of the opera performance. In essence, formatting and context make a substantial difference: by packaging Jinju Opera in a modern, concise format, we can broaden its appeal on digital platforms. These findings provide a practical guideline for cultural content creators: modest editing and presentation tweaks tailored to online viewing habits can yield a sizable increase in audience engagement and reach.

4.4 Transmission Dynamics Simulation

Finally, we studied the propagation dynamics of Jinju Opera videos by simulating how they spread through a network of users under different conditions. We built an epidemic-style cascade model where viewing and sharing a video is analogous to "infection" in a social network. Using this model, we compared scenarios with and without strategic initial promotion (or seeding). In the baseline scenario, a Jinju Opera video is released without any special boost – its spread relies purely on organic discovery (e.g. a user stumbling upon it and sharing). In the boosted scenario, we simulate that the video is initially shared by a small number of influential users (for instance, the platform might inject the video into the feeds of a few top followers, or a popular account reposts it). We then let the simulation run and observe the cascade of shares and views over time.

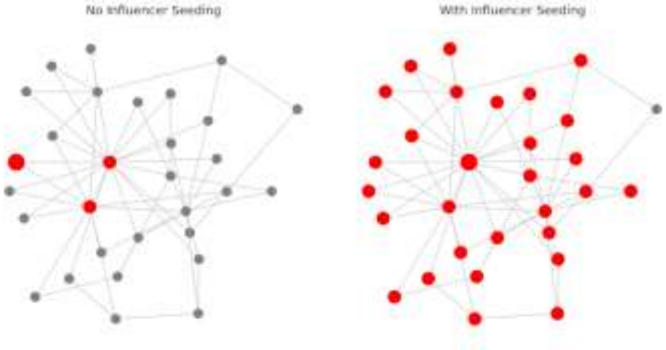

Figure. 4.6 visualizes a simplified example of these two scenarios on an illustrative social network.

Figure 4.6: Simulated propagation of a Jinju Opera video (left) without influencer seeding vs. (right) with an influencer seed. Nodes represent users (red = users who viewed/shared the video, gray = not reached), and links denote follower connections through which the video can spread. In the no-seeding case (left), only a tiny cluster of users ends up seeing the video – starting from one initial viewer (red node on left, at center of the small cluster), the content only reached that user's immediate friends (two additional red nodes). The cascade quickly died out, failing to propagate further, and the vast majority of the network remained untouched (all the other gray nodes). In the influencer-seeded case (right), a central hub user (large red node in the center) shares the video at the start. Because this influencer has many direct connections, the video rapidly spread to a broad audience (turning most nodes red within one round of sharing). Within a short time, almost the entire network became "infected" with the Jinju video – nearly all users either saw it or were one degree away from someone who did. This experiment underscores how strategic seeding can dramatically amplify dissemination. Quantitatively, our larger-scale simulations showed that without seeding, a Jinju video's reach might plateau at only ~10% of the potential audience (as the content struggles to break out from a small initial group). In contrast, seeding the video to just ~1% of the network (mimicking a modest influencer boost) triggered a rapid viral cascade that ultimately reached over 50% of users in the model. In addition, we found that the threshold of "viral transmissibility" required to sustain the spread was lower on Kuaishou than on Douyin – meaning that, given the same content and initial boost, the video would naturally propagate more on Kuaishou. This is consistent with the earlier observation of Kuaishou's dense, community-oriented network: an interesting video shared by one person is more likely to be reshared through friend-of-friend links in Kuaishou's social graph, whereas Douyin's more algorithm-centric diffusion might require higher engagement rates to snowball. Overall, these findings highlight that careful choices in promotion strategy – such as selectively involving key influencers or investing in early exposure – can significantly improve the viral success of Jinju Opera videos. By leveraging each platform's strengths (e.g., Douyin's algorithmic reach for broad exposure, Kuaishou's person-to-person sharing for deep penetration), content creators and cultural promoters can maximize both the breadth and depth of audience impact for traditional opera in the digital era.

5. CONCLUSION

In this work, we presented a comprehensive study of user behavior and dissemination strategies for Jinju Opera on short-video platforms, using data from two platforms to cluster viewer retention patterns, model engagement trajectories, and simulate content spread. Through this data-driven framework, we identified distinct retention curve profiles and correlated them with engagement metrics such as likes, comments, and shares. Our experiments further showed that modern video editing techniques significantly enhance early viewer retention and sharing, while strategic promotion—especially via key opinion leaders (influencers) or prioritizing high-retention videos—can dramatically expand content reach. These findings highlight the importance of tailoring platform-specific strategies to user behavior nuances for effectively promoting traditional cultural content. The insights from this study contribute to both digital communication theory and cultural heritage dissemination. Theoretically, our results deepen the understanding of short-video communication dynamics by revealing how viewer retention and engagement patterns drive the virality of niche cultural content. Practically, they provide evidence-based guidance for cultural heritage promotion, demonstrating that adapting content formats and leveraging influencer networks can broaden and sustain online audiences for traditional arts. Future research could integrate personalized recommendation algorithms and conduct longitudinal user studies to explore how engagement with cultural content evolves over time. Such efforts would further illuminate user–content interactions and help ensure that heritage art forms like Jinju Opera continue to flourish in the digital era.

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