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From Connectivity to Commercialization: How High-Speed Networks Reshape Short-Video and Live-Streaming Media

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Abstract. The evolution of high-speed networks, from 4G to 5G and toward 6G, has profoundly reshaped online media. Short-video and live-streaming platforms have become dominant forms, supported by low latency, high bandwidth and ubiquitous connectivity. This paper examines three questions: how high-speed networks affect short-video media, how they affect live-streaming media, and what distinguishes the two in recommendation mechanisms and commercial conversion. It develops a conceptual framework with illustrative simulations and a descriptive case. The study first outlines core technical affordances. It then analyzes short-video media, focusing on content production, dissemination, and a simplified fixed-content scoring model, explored through a logistic-regression simulation. The discussion subsequently turns to live streaming, introducing live-specific algorithms and a time-varying feedback loop from content to commercialization, illustrated by a manually compiled handicraft case. This study also addresses challenges, including the digital divide, bandwidth pressure, and content moderation, and outlines future directions toward 6G and AI-driven optimization. These findings offer a reference framework for sustainable digital media development and cultural dissemination.

Keywords: High-speed Internet, Short-form Video, Live-stream Broadcasting, Recommendation Algorithm, Digital Media

1. Introduction

Over the past two decades, communication technology has evolved from 2G/3G to 5G, delivering up to 1 Gbps and allowing entire movies to download within seconds. The forthcoming 6G era promises ultra-low latency and ultra-high bandwidth, enabling real-time holographic broadcasting and highly interactive virtual reality. This trajectory has laid a solid foundation for online cultural content and media services. Traditional media, such as written news and low-quality video, were constrained by early networks' inability to handle large-scale data, leaving diverse cultural needs unfulfilled. High-speed networks now overcome these limits, enabling smooth transfer of large video files at low cost and spurring the rapid growth of new media.

Short videos and live broadcasts have become common ways to be entertained and gain knowledge, fitting into brief periods of free time, such as during commutes, work breaks, and waits in queues. Platforms like Douyin, Kuaishou, Bilibili, and YouTube continuously adjust services according to network capabilities—optimizing video quality dynamically, incorporating low-latency

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interactive functions, and adapting content formats. This links network advancement closely to daily cultural consumption.

This paper examines three interrelated questions: First, how do high-speed networks shape short-video media? Second, how do they shape live-streaming media? Third, what distinguishes the two in recommendation mechanisms and commercial conversion? To address these questions, the paper first outlines the core technical traits of high-speed networks—short latency, wide bandwidth, and dependable connectivity—along with supporting mechanisms such as edge computing, adaptive bitrate streaming, and network slicing. It then analyzes short-video media, focusing on content production, dissemination, and a simplified fixed-content scoring model expressed as

$$\text{Score} = \Sigma \text{Pi} \times \text{Vi} \tag{1}$$

explored through a logistic-regression simulation. The discussion subsequently turns to live streaming, introducing adaptive bitrate protocols and live-specific algorithms, such as Moment & Cross, TSSTFN and SL-MGAC, and outlines a recursive loop: Content→Algorithm→Engagement→ Algorithm→Commercialization. Finally, the paper synthesizes the challenges—digital divide, bandwidth pressure, and content moderation—and outlines future directions towards 6G and AI-driven network optimization. By clarifying the relationship between network capacity and media applications, this paper offers a foundation for further exploration of industry impacts and future media consumption behaviors.

2. Analysis of high-speed network technology's technical affordances

2.1. Core technical features of high-speed networks

High-speed network systems have three key technical features: high bandwidth, low latency, and widespread connectivity. These innovative technological attributes represent a fundamental evolution of cellular communication architecture, rather than a simple upgrade from previous mobile network generations [1]. Bandwidth may be regarded as the data-transfer capability of a network system. Higher bandwidth enables greater data throughput, which is crucial for sending high-definition and 4K media content without glitches or buffering. Latency indicates the time lag of data transfer between endpoints. In scenarios supported by 5G, the latency can be decreased to the millisecond scale, which ensures immediate responses for real-time interactions like live commenting and cloud collaboration [2]. Ubiquitous connectivity implies that users are able to access network services steadily in various scenarios via an extensively covered communication infrastructure. These three advantages jointly provide reliable technical conditions for the fast growth of the short video and live broadcast industry, and continue to promote new ways of content delivery and user interaction.

2.2. Technical support for media transmission

High-speed networks depend on three fundamental mechanisms for dealing with media content delivery. First, edge computing significantly reduces transmission latency by processing data directly at the network edge rather than on remote servers. This is crucial for preventing disruptions to live streaming [3]. Second, adaptive bitrate streaming technology modifies the video quality instantaneously according to the real-time network status. This prevents buffering or stuttering when the signal becomes patchy. Furthermore, 5G network slicing provides a dedicated priority channel

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for media services, ensuring live comments and interactive features have prioritized access to bandwidth. This not only improves the user's experience but also enables the entire service to operate more smoothly. Collectively, these technological frameworks and infrastructure components create a robust support system, guaranteeing that users can enjoy smooth, high-quality short videos and live broadcasts.

3. Impact on short video media

3.1. Changes in content production

High-speed networks greatly lower barriers to short-video creation, while cloud editing tools and real-time preview serve as important auxiliary means. This technological change has redefined the hardware needs for content creation. Rather than depending on high-performance local workstations, content creators currently transfer computationally demanding tasks like video rendering, multi-track editing, and special effects processing to remote cloud servers [4]. This decentralized computing architecture efficiently alleviates hardware limitations that previously restricted creative participation [4].

The resulting democratization of content creation is manifested in two dimensions. First, cloud-based editing tools eliminate the need for high-performance local workstations, as computationally demanding tasks are transferred to remote servers. A 2025 IEEE study demonstrates that AI-accelerated cloud pipelines reduce 60-second video production costs from $150-300 to $15-40, a 90% decrease, while cutting production time by 85% [5]. Secondly, browser-based interfaces and low-latency networks enable non-expert users to access high-end editing functions and engage in real-time collaborative editing that transcends geographical limitations.

Empirically, the shift toward cloud-enabled mobile creation is evident in platform data. By August 2023, 490 million users worldwide were using CapCut (TikTok's official editing app), approximately 25% of TikTok's 2.1 billion global users, and total user spending on video editing apps reached $610 million in 2023, a 27% year-over-year increase [6]. This change enriches content storytelling and improves cultural portrayal by amplifying voices from previously marginalized areas. The technological framework, therefore, acts as both an enabler for creative manifestation and a catalyst for digital integration, transforming the power dynamics within the media ecosystem.

3.2. Changes in content dissemination

In recent years, the widespread deployment of high-speed networks has significantly improved both connectivity and reliability. This technological advancement has greatly facilitated the extensive dissemination of short-form video content, enabling viral spread at a much faster rate than previously possible. Platforms are now capable of distributing videos to millions of users simultaneously with minimal loading delays, which supports the rapid rise of new content and allows trending clips to gain widespread attention within one day instead of taking weeks. From a technological perspective, short-form videos are optimized to operate seamlessly on mobile networks. Designed to load rapidly even under unstable signal conditions, they align with the fragmented nature of modern mobile media consumption, such as brief viewing sessions during commutes, lunch breaks, or while waiting in line. This adaptation caters to the widespread constant connectivity observed among contemporary users, who increasingly prioritize concise, accessible content over lengthy, drawn-out formats.

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Improved technological infrastructure and evolving content formats are not merely operating in parallel; they are mutually reinforcing. Enhanced networks enable creators to produce more engaging content, such as AR filters and live polls, which in turn increases user engagement with these platforms. Simultaneously, growing demand for more advanced interactive features drives companies to invest in superior network technologies, including 5G Advanced and satellite internet. This creates a cyclical relationship that expands the digital content ecosystem, offering expanded avenues for video creation, distribution, and engagement [7].

3.3. Network and algorithmic influences on viewing behavior

Media consumption patterns have been fundamentally reshaped by the advancement of high-speed internet technology. People can now watch short videos seamlessly at any time and from any place, with hardly any buffering problems. This change brings more than just convenience and reshapes the entire media environment. From an academic perspective, network delay directly affects user retention on short-video platforms. Research indicates a distinct relationship: faster loading speeds result in longer viewing periods and greater user retention [8]. For instance, when the time it takes to load videos falls below 2 seconds, user interaction goes up by 40%—a vital metric for platform administrators.

Thus, enhancing infrastructure is not merely about getting platforms to operate more effectively. It strengthens user loyalty. Eliminating disruptive buffering significantly promotes sustained video engagement, particularly during fragmented daily routines, including commutes, queuing, and short work breaks. This seamless viewing experience transforms occasional viewers into frequent users.

Beyond network performance, short-video platforms rely on a core ranking algorithm to distribute content to active users, known as the recommendation priority formula. Its simplified form can be expressed as:

$$\text{Score} = \Sigma \text{Pi} \times \text{Vi} \tag{2}$$

where Score denotes the final recommendation priority score of a video; P_i represents the predicted probability of the i-th user behavior; and V_i is the predefined value weight assigned to this behavior by the platform. The algorithm predicts multiple user behaviors, such as likes, comments and shares, and multiplies each predicted probability by its corresponding weight to calculate a composite score. Videos with higher scores obtain higher exposure priority. Table 1 demonstrates a numerical calculation example with preset weights (V_{like}=0.5, $V_{comment}$=1.0, V_{share}=2.0). This table is purely illustrative. To assess the ranking validity of the static scoring formula, a computational simulation was conducted rather than a randomized human-subject experiment. Synthetic data were generated for video features and user behaviors, and logistic regression classifiers were trained to predict behavior probabilities, which were then combined via the weighted sum to produce composite scores and rankings. This simulation tests the internal consistency of the formula under controlled assumptions but does not establish causal effects of network latency on user behavior. The positive relationship between network delay and user retention reported earlier is based on prior literature [6].

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Table 1. Numerical illustration of the recommendation priority score computed by the weighted sum of predicted user-behavior probabilities

Video	Predicted like probability Plike	Predicted comment probability Pcomment	Predicted share probability Pshare	Composite Score	Ranking
A	0.7	0.3	0.1	0.85	3
B	0.3	0.6	0.4	1.55	1
C	0.5	0.5	0.2	1.15	2

This multi-objective ranking mechanism reshapes global user behavioral patterns. A high-speed network removes playback interruptions and raises the baseline probability of user interactions. These elevated predicted probabilities are then fed into the recommendation formula, further lifting videos' recommendation scores and boosting content exposure. Modern audiences increasingly expect immediate, uninterrupted access to information and entertainment; platforms failing to deliver smooth streaming and effective recommendation algorithms will fall behind in market competition. This transformation is not merely technical but reshapes media consumption behaviors on a worldwide level.

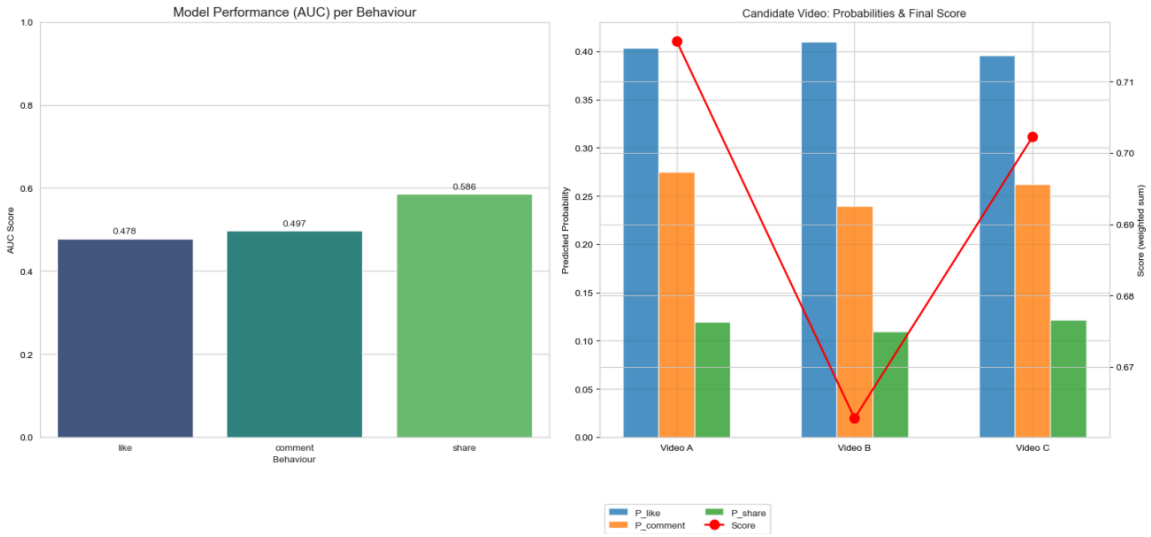


Figure 1. Illustration of the multiobjective video recommendation priority framework. (a) Model performance comparison; (b) Candidate ranking analysis

The bar chart in Figure 1(a) shows the AUC values for three independent binary classifiers predicting user interactions (like, comment, and share); the grouped bars in Figure 1(b) represent the predicted probabilities for each behaviour (P_{like}, $P_{comment}$, P_{share}), while the red line with markers indicates the final comprehensive priority score computed as $Score=\sum_i w_i \cdot p_i$, with weights set to $\omega_{like}=0.5$, $\omega_{comment}=1.0$, and $\omega_{share}=2.0$. According to the computed scores, Video B receives the highest recommendation priority.

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4. Impact on live streaming media

4.1. Improvements in streaming stability and clarity

High-speed networks have fundamentally transformed live streaming, substantially reducing buffering and enabling ultra-high-definition video delivery. Technologically, this relies on adaptive bitrate (ABR) streaming, e.g., MPEG-DASH and HLS, which dynamically adjusts resolution based on real-time bandwidth and buffer occupancy, alongside low-latency extensions (LL-DASH/LL-HLS) that cut end-to-end latency to under 4 seconds through chunked transfer [9]. 5G deployment exemplifies this, reliably supporting 4K and even 8K broadcasts with minimal delay, eliminating previous freezing issues and creating immersive experiences for concerts, sports and esports.

Beyond transmission, the recommendation logic for live streaming differs markedly from that of short-video platforms. Short-video systems typically employ a static scoring formula:

$$\text{Score} = \sum \text{Pi} \times \text{V i} \tag{3}$$

where P_i are predicted probabilities of user actions (like, comment, share) and V_i are platform-assigned weights. Live streaming introduces dynamic content evolution, real-time feedback, bilateral optimization and severe data imbalance. To address these challenges, platforms have deployed several advanced models: Kuaishou's Moment & Cross performs cross-domain CTR prediction using short-video behavior signals; Douyin's Time-Slice level Spatial-Temporal Fusion Network (TSSTFN) captures minute-level temporal dependencies through its spatial-temporal fusion module; and the Supervised Learning-enhanced Multi-Group Actor Critic (SL-MGAC) algorithm determines optimal live-stream insertion moments [10]. These algorithms jointly optimise engagement and retention in real time.

Seamless streaming raises baseline interaction probabilities, which feed into the multi-objective formula, boosting scores and exposure. Platforms failing to deliver both smooth delivery and intelligent recommendations will inevitably lose their competitive edge.

4.2. The feedback loop from content to commercialization

Live streaming platforms operate based on a recursive closed-loop mechanism, in which content and streamer characteristics serve as the foundational inputs for algorithmic traffic distribution. Specifically, streamers' historical commercial performance and previous audience interaction quality determine the initial traffic resources allocated by the platform algorithm. This baseline traffic exposure generates continuous real-time user engagement signals, which are captured and analysed by the system to trigger secondary algorithmic adjustments, ultimately translating dynamic user behaviours into final commercial outcomes such as viewer purchases, virtual gifts, and total gross merchandise value (GMV). To formalise this multi-stage feedback process, the present study defines a complete set of theoretical variables with unified symbolic specifications.

At the content and streamer stage, X_2 represents historical GMV and X_4 denotes the past engagement rate, both of which function as core static attributes that influence initial algorithmic weighting. At the initial algorithmic allocation stage, T_0 refers to the baseline traffic volume assigned to each live stream, measured in logarithmic form to reduce distributional skewness. In terms of real-time user engagement, E_{t-1} stands for lagged historical engagement that reflects cumulative audience activity, while Decay_t represents engagement decay that captures declining user interest over streaming time. In the secondary algorithm optimisation stage, $\overline{\Delta T}$ is defined as the

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average traffic adjustment magnitude, which reflects the degree of real-time algorithmic amplification or suppression. These sequentially structured variables and their theoretically expected directional relationships are systematically illustrated in Table 2.

Table 2. Variables and expected effects in the feedback loop

Stage	Variable	Symbol	Expected sign on next stage	Rationale
Content/Anchor	Historical GMV	X_2	+	Higher past sales attract larger initial traffic
Content/Anchor	Past engagement rate	X_4	$+_0$	Algorithm favours interactive content
Algorithm (initial)	Initial traffic (log)	$\ln(T_0)$	+	More exposure generates more interaction opportunities
Engagement (real-time)	Lagged engagement	E_{t-1}	+	Positive feedback triggers traffic amplification
Engagement (real-time)	Engagement decay	$Decay_t$	-	Declining interest reduces subsequent allocation
Algorithm (re-optimisation)	Average traffic adjustment	$\overline{\Delta T}$	+	Dynamic adjustment boosts final commercial outcomes

Note: This table presents theoretically hypothesised constructs and directional relationships synthesised from live-streaming commerce and recommendation system literature. All expected effects represent theoretical predictions rather than empirically estimated coefficients.

Based on the above variable definitions and theoretical framework, this study proposes a reduced-form empirical specification to examine the association between algorithmic re-optimisation and commercial outcomes. This is a proposed specification rather than a report of completed regression results. The specification is structured as follows:

$$Yi = \beta 0 + \beta 1 \ln(T0i) + \beta 2\overline{E}i + \beta 3\Delta Ti + \gamma 2Xi + \varepsilon i \quad (4)$$

In this formula, Y_i denotes the final commercial output of each live stream, corresponding to total GMV and gift revenue; T_{0i} represents the algorithm-assigned initial traffic volume; $\overline{E}_i$ indicates the average segment-level user engagement synthesised from bullet comments and virtual gift behaviours; $\overline{\Delta T}_i$ is the average dynamic traffic adjustment within a single live session; X_{2i} refers to individual streamers' historical GMV level; β_0 is the constant term; β_1, β_2, β_3 and γ are estimated coefficients; and ε_i represents the random error term. This study hypothesises that the core coefficient β_3 is significantly positive, indicating that real-time interaction-driven algorithmic adjustment effectively improves live-stream commercial performance. This multi-stage feedback design explains how static content characteristics and dynamic algorithmic adjustments jointly shape platform commercialisation, providing a robust theoretical and model foundation for mechanism analysis.

In this proposed specification, Y_i denotes the final commercial output of each live stream. To avoid mechanical overlap with engagement measures, two separate dependent variables are defined

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and estimated: GMV_i , representing total gross merchandise value, and $Gift_i$, representing total virtual gift revenue. T_{0i} represents the algorithm-assigned initial traffic volume, measured as the number of initial impressions or viewers allocated at the start of the stream; its natural logarithm $\ln(T_{0i})$ is used to reduce distributional skewness. $\overline{E}_i$ denotes average segment-level user engagement over the entire live session, computed as the mean of non-monetary interactions—bullet comments, likes, and shares—across fixed-length one-minute segments, excluding virtual gifts to prevent mechanical overlap with $Gift_i$. $\overline{\Delta T}_i$ is the average dynamic traffic adjustment within a single live session, calculated as the mean change in impressions per one-minute segment relative to the previous segment. X_{2i} refers to the streamer's historical GMV level and serves as a control for streamer-level heterogeneity; additional controls such as content category, time of day, and device or network conditions should be included where data permit. β_0 is the constant term; β_1, β_2, β_3 and γ are estimated coefficients; and ε_i represents the random error term. We hypothesise that $\beta_3>0$, but emphasise that this is a theoretical prediction rather than an empirically confirmed effect. Table 2 presents the expected signs; the expected sign for past engagement rate should be corrected to "+" rather than "+0". Because initial traffic, real-time engagement, and commercial outcomes may be jointly determined, and because no exogenous variation is introduced, this specification cannot identify causal effects. The model therefore captures conditional associations only. The temporal ordering—initial allocation, subsequent engagement, traffic adjustment, and final sales—provides a descriptive framework rather than a causal identification strategy. This multi-stage feedback design illustrates how static content characteristics and dynamic algorithmic adjustments are associated with platform commercialisation, offering a foundation for future empirical estimation.

4.3. Algorithmic traffic allocation and commercial outcomes

High-speed networks have transformed live-streaming commerce by enabling ultra-HD product displays, real-time flash sales, and interactive promotions that drive immediate purchases [11]. Virtual events further reduce costs and expand global reach. Crucially, algorithmic traffic allocation determines which streams gain high exposure. Unlike short videos with independent traffic, live streams receive a daily initial budget and advance through tiers based on real-time performance.

To illustrate, we examine an anonymised handicraft brand's official live stream on a major short-video platform (hereafter Platform A). The data were manually compiled from publicly accessible platform records on a single session observed on 15 March 2026. Screenshots and timestamps of the live dashboard were retained for verification; the platform name is withheld to comply with anonymity conventions. The streamer had 850K followers, streamed daily for 3 hours during peak time (20:00–22:00), and ranked in the top 8% of the artisan category by historical GMV. The platform's algorithm allocated approximately 35,000 initial viewers, measured as cumulative unique viewers within the first 5 minutes of the stream. Within the first 15 minutes, the comment rate (14% of viewers in that 15-minute window), like rate (58% of viewers in the same window), and gift density triggered a tier upgrade, expanding cumulative unique viewers to 120,000 by minute 30 and to 280,000 by the end of the session. The session generated 620K RMB in GMV during the live broadcast. Because only a single case is observed and no exogenous variation is introduced, the observed revenue cannot be causally attributed to algorithmic amplification; the evidence is descriptive and consistent with an association between tier upgrades and commercial outcomes. By contrast, streams with low engagement (below 3% interaction rate or 30% watch-time ratio) are typically subject to traffic capping, consistent with the self-reinforcing loop: Content→ Algorithm→ Engagement→ Algorithm→ Commercialization.

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Table 3 summarises the key determinants of high-traffic recommendations.

Table 3. Factors affecting live-stream traffic allocation

Factor	Key Metric	Effect on Traffic
Followers	Count (>500K)	Higher initial weight
Streaming Duration	≥3h/day, ≥5d/week	Signals stability, boosts priority
Category	High-GMV (beauty, 3C)	Favoured in transaction-weighted models
Time of Day	Peak hours (20:00–22:00)	Matches user activity, enhances exposure
Historical Engagement	Watch time >5 min, interaction >10%	Determines next session's initial traffic
Comments	Comment/viewer ratio >15%	Triggers tier upgrade
Likes	Like/viewer ratio >50%	Improves real-time score
Network Quality	≥1080p, <2s latency	Poor quality reduces recommendation weight

These factors collectively shape the feedback mechanism: successful commercial performance feeds back into the traffic allocation of subsequent live sessions, forming a virtuous cycle for high-performing live streams.

The distinction between live streaming and short-video recommendation extends beyond traffic allocation to the nature of content consumption. Short-video content is relatively fixed once uploaded, and the platform typically allocates baseline traffic based on pre-computed engagement probabilities, producing delayed and discrete feedback from likes, comments, and shares [12]. Live streaming, by contrast, is dynamic and real-time. Content evolves continuously, and a stream that is engaging at one moment may lose appeal the next. The recommendation algorithm must therefore monitor minute-level signals—bullet comment density, gift frequency, watch-time ratio—and adjust traffic allocation on the fly. This creates a bilateral optimisation problem: the platform must simultaneously retain viewers and sustain streamers, jointly considering real-time content evolution and the mutual influence between streamers and audiences [13]. Moreover, commercial conversion differs fundamentally: short-video purchases are often delayed (link clicks, saved carts), whereas live streaming enables immediate transactions (impulse purchases, tipping). Recent work also recognises that short-video recommendation increasingly incorporates creator-side incentives alongside user engagement, moving toward multi-stakeholder optimisation [14]. These contrasts explain why the feedback loop: Content→ Algorithm→ Engagement→ Algorithm→ Commercialization is more pronounced in live streaming than in a fixed-content short-video scoring model, though the two settings are not mutually exclusive and short-video systems are also evolving toward time-aware designs.

5. Synthesis, challenges and future directions

The preceding analysis addressed three questions: how high-speed networks reshape short-video media, how they transform live streaming, and what distinguishes the two. Short-video recommendation often relies on relatively fixed content features and pre-computed engagement probabilities, with feedback typically occurring after viewing; however, recent systems increasingly

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incorporate creator-side incentives alongside user engagement. Live streaming, by contrast, involves time-varying content and requires real-time monitoring of signals, such as bullet comment density, gift frequency, and watch-time ratio, with traffic adjustments that may consider both viewer retention and streamer sustainability. This helps explain why the feedback loop Content→Algorithm →Engagement→Algorithm→Commercialization tends to be more pronounced in live streaming than in a fixed-content scoring model. Yet challenges persist. Not every individual has equal access to high-speed internet; remote rural areas and low-income areas fall far behind in network coverage quality, exacerbating the digital divide. Consequently, these groups face disadvantages in accessing and exchanging information [15]. Simultaneously, soaring data traffic strains existing network capacity, and rapid transmission accelerates the spread of harmful and false information, demanding continuous infrastructure investment and rigorous content moderation.

Looking forward, 6G networks are going to transform the internet media ecosystem in ways that we have just begun to conceive. The technology's most prominent advantage—ultra-low transmission latency and ultra-high data bandwidth—will eventually transform futuristic concepts such as real-time holographic broadcasting and highly interactive virtual reality short videos into everyday media experiences. From a technical perspective, AI-powered network optimization algorithms will render media content transmission much more efficient and dependable. The growing demand for personalized and on-demand media consumption has been recognized as an irreversible long-term trend within the digital media industry, driven by evolving user behavioral habits across diverse mobile network environments [16]. For short video, these advances will further lower production barriers and accelerate dissemination; for live streaming, they will enable richer real-time interactivity and intensify bilateral optimization. Striking a balance between innovation and appropriate regulation will remain essential as technology progresses.

6. Conclusion

High-speed network technology has driven the upgrading of short-video and live-streaming media, reshaping the digital media value chain from creation to commercialization. Reduced creation barriers enhance diversity; improved dissemination accelerates cultural circulation; enriched interactivity boosts engagement. However, challenges persist: uneven network resource distribution, infrastructure pressure, and complex content supervision require systematic governance and a balance between innovation and regulation.

This study offers conceptual and illustrative contributions. Theoretically, it integrates literature on network affordances, recommendation algorithms, and live-streaming commerce to propose a unified framework. It contrasts a simplified fixed-content scoring model for short video with a time-varying live-streaming setting, and outlines the recursive loop Content→ Algorithm→ Engagement→ Algorithm→ Commercialization with defined variables and a proposed reduced-form specification. Illustratively, it presents a logistic-regression simulation of like, comment, and share behaviours to compute, $\text{Score} = \sum \text{Pi} \times \text{V i}$, with AUC comparisons and candidate rankings to explore the internal consistency of the static scoring formula. It also uses manually compiled platform data for a handicraft live-streaming case, illustrating initial traffic allocation, tier upgrades from real-time engagement, and final commercial outcomes. These strands jointly show how static content characteristics and dynamic algorithmic adjustments are associated with platform commercialization, without claiming causal identification. Future trends include immersive visuals, intelligent dissemination, and multi-dimensional interaction. Future research can explore novel network technologies and industry ecosystem improvement.

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