

A Dynamic AI Framework for Monitoring and Forecasting Media Convergence Competitiveness

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Abstract: In response to the limitations of traditional static and subjective methods, this study pioneers an AI-driven framework for assessing media convergence competitiveness by leveraging natural language processing and machine learning. Analyzing a large-scale dataset of YouTube comments from January to June 2024, the research employs sentiment classification models—including Support Vector Machine, Random Forest, and Gradient Boosting—with Gradient Boosting demonstrating superior performance. The findings reveal that the proposed framework not only outperforms conventional approaches in accuracy and consistency but also captures nuanced public sentiments and their temporal dynamics, uncovering a dual pattern of instant emotional reactions and reflective long-term evaluations. This provides policymakers and media practitioners with a scalable, data-driven tool for real-time assessment and evidence-based strategy formulation. Ultimately, the study underscores the transformative potential of integrating computational social science with media studies, significantly enhancing the precision and predictive power of competitiveness evaluation beyond qualitative paradigms.

Keywords: Natural language processing (NLP); Sentiment analysis; Gradient Boosting; Media convergence competitiveness.

1. Introduction

The rapid advancement of digital technologies has fundamentally transformed the media ecosystem, catalyzing the emergence of media convergence. Defined as the integration of technological platforms, content production, and user interactions across multiple channels, media convergence enables organizations to amplify their influence and maintain competitive advantage in an increasingly fragmented environment (Keskin, 2018). As the boundaries between traditional broadcasting, streaming services, and social platforms continue to blur, the capacity to accurately evaluate media convergence competitiveness has become a pressing issue for both academics and industry practitioners.

Recent scholarly work has largely centered on structural and industrial facets of media convergence—such as technological infrastructure, regulatory frameworks, and platform strategies (Kazak et al., 2018; Napoli, 2019). Although these studies offer valuable insights, they predominantly rely on static metrics such as financial performance, audience ratings, or content output. Such indicators fall short of capturing the dynamic and real-time nature of competitiveness, which is increasingly influenced by user perceptions and interactive behaviors on social platforms (Zhou & Zhang, 2023). Against the backdrop of proliferating user-generated content, social media now presents unprecedented opportunities to gauge competitiveness through the lens of audience sentiment and participatory engagement.

To bridge this gap, this study examines user comments from YouTube spanning the period from January 1 to June 30, 2024. As a hybrid platform for both content dissemination and social interaction, YouTube constitutes an ideal empirical context: its comment sections encapsulate not only immediate

affective responses but also more sustained evaluative discourses. By employing a suite of machine learning techniques—including decision trees, random forests, and multilayer perceptron—this research aims to assess whether computational methodologies can enhance the precision and predictive validity of competitiveness measurement.

This study offers three principal contributions. First, it refines the conceptual framework of media convergence competitiveness by synthesizing technological, content-related, and user-interactive dimensions into a cohesive model. Second, it introduces a methodological innovation through the application of machine learning to large-scale social media data, thereby advancing the operationalization of competitiveness. Third, it furnishes empirical evidence derived from YouTube data, demonstrating that AI-driven methodologies significantly improve both the accuracy and forward-looking capacity of competitiveness assessment. Together, these contributions not only deepen the theoretical discourse but also provide actionable intelligence for media stakeholders and policymakers operating in an evolving digital landscape.

2. Literature Review

2.1. Media Convergence and Competitiveness

Media convergence is conceptualized as the integration of traditional and digital media through intertwined technological, organizational, and cultural processes (Jenkins, 2006; van Dijk, Poell, & de Waal, 2018). This convergence fundamentally reconfigures the entire media lifecycle—from content creation and distribution to consumption—fostering novel modes of audience participation and intensifying competitive dynamics. Consequently, competitiveness in this domain transcends conventional metrics like market share

and financial performance, encompassing a platform's capacity for technological innovation, user engagement, and adaptability to rapidly evolving market conditions (Napoli, 2019; Chen & Li, 2023). While prior research affirms that media convergence enhances industry-wide adaptability, a critical gap remains in understanding the dynamic interplay between technological innovation and user engagement—two pivotal, yet underexplored, drivers of digital competitiveness (Kim, 2019).

2.2. Measuring Media Competitiveness: From Static Indicators to User Perspectives

Conventional frameworks for evaluating media competitiveness have predominantly been anchored in retrospective and static indicators, such as financial metrics, content output, and advertising revenues (Doyle, 2013; Zhou & Zhang, 2023). While these measures offer valuable historical insights, they inherently lack the capacity to capture the dynamics of real-time audience engagement or to furnish predictive insights into future competitive standing. Furthermore, the prevailing scholarly focus has often centered on media firms as organizational entities, thereby overlooking the granular, user-level perceptions articulated on interactive platforms like YouTube. Such user-generated commentaries, however, constitute a rich and dynamic data source, offering a window into how audiences contemporaneously evaluate media performance, content quality, and competitive positioning (Hu, Li, & Lee, 2023). It is this critical gap that the present study seeks to address by reorienting the analytical emphasis from top-down institutional strategies to bottom-up, user-driven evaluations of competitiveness.

2.3. User-Generated Content as a Data Source for Competitiveness Assessment

The ascendancy of social media platforms has fundamentally reconfigured user roles, transforming them from passive consumers into active participants who generate massive volumes of user-generated content (UGC). Scholars increasingly posit UGC as a critical proxy for gauging public sentiment, assessing platform competitiveness, and discerning broader industry trends (Mehmood, Verleye, De Keyser, & Lariviere, 2024). Within this landscape, YouTube comments, in particular, offer a real-time repository of audience reactions, yielding invaluable insights into user engagement patterns, emergent cultural trends, and the relative competitive standing of media platforms. Despite its demonstrable potential, the systematic integration of UGC into formal frameworks for competitiveness assessment remains a notably underdeveloped area of research.

2.4. Advances in AI and Predictive Approaches

Recent scholarly work underscores the increasingly pivotal role of artificial intelligence (AI) and machine learning (ML) in advancing media research (Jordan & Mitchell, 2015; Zhang & Ma, 2022). AI-driven models facilitate real-time data processing, nuanced sentiment detection, and proactive trend forecasting, thereby offering a distinct competitive advantage over conventional evaluative methodologies. Nonetheless, the predominant application of these techniques remains confined to domains such as recommendation systems and content personalization (Chan-Olmsted, 2019; Mastorakis et al., 2020), with their systematic deployment for assessing media convergence competitiveness still in its nascent stages. We contend that by leveraging algorithms capable of

synthesizing multiple dimensions—technological innovation, content distribution, user engagement, and market adaptability—research can attain superior predictive accuracy and heightened practical relevance.

In synthesizing the extant literature, it is evident that while the significance of media convergence and its competitive ramifications is well-established, several critical shortcomings persist. First, prevailing assessment frameworks disproportionately depend on static indicators, failing to incorporate dynamic, real-time user feedback. Second, despite the recognized predictive potential of AI, its application within competitiveness evaluations remains markedly underutilized. Finally, the scholarly emphasis has predominantly been placed on media organizations as entities, thereby marginalizing user-level evaluations and overlooking the constitutive role of audience perception in shaping competitive outcomes.

To address these identified gaps, this study constructs a machine learning-based framework for assessing media convergence competitiveness, empirically grounded in YouTube user comments from January to June 2024. Accordingly, this research is guided by the following questions:

RQ1: To what extent can machine learning models enhance the precision and predictive performance of media convergence competitiveness assessments relative to traditional methods?

RQ2: What are the pivotal dimensions that constitute and contribute to media convergence competitiveness in the contemporary digital ecosystem?

RQ3: In what ways can the proposed machine learning model facilitate real-time strategic decision-making and improve the forecasting of future trends in media competitiveness?

3. Methodology

3.1. Research Framework

This study proposes an AI-driven framework for evaluating media convergence competitiveness, structured around four critical dimensions: technological innovation, content distribution, user engagement, and market adaptability. Designed to integrate real-time social media data with advanced deep learning architectures, the framework aims to surpass traditional evaluation methods by delivering enhanced precision and robust predictive capability. As illustrated in Figure 1, the entire process—from initial data collection to the final AI-based evaluation—constitutes a systematic and comprehensive tool for assessing media convergence competitiveness in the digital age.

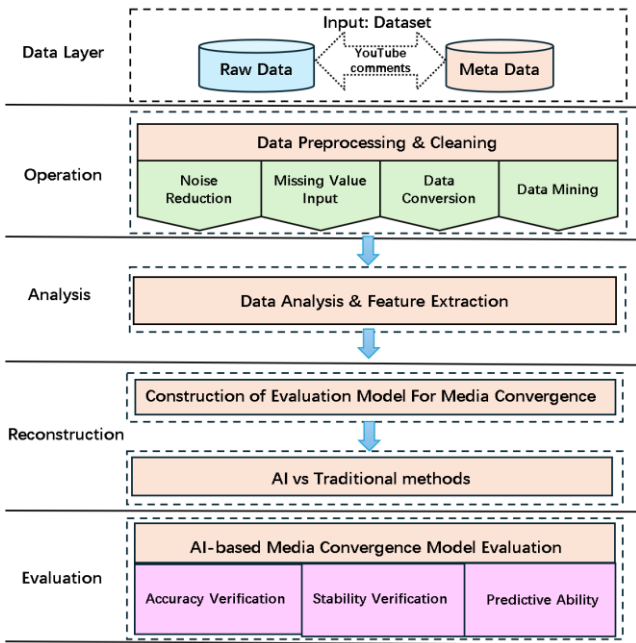


Figure 1. The overall process of media convergence competitiveness system framework

3.2. Data Resources

As the world's preeminent video-sharing platform, YouTube generates massive volumes of user comments on a daily basis. These data are characterized by multilingual content, informal expressions, emojis, hashtags, and a significant proportion of spam, collectively presenting considerable challenges for scholarly analysis. This study draws upon comments posted during the first half of 2024 (January 1 to June 30). The original dataset comprised over 51 million records spanning multiple languages. To ensure data integrity, a rigorous preprocessing pipeline was implemented, involving language standardization, spam filtering, duplicate removal, and extraction of English-language content. This procedure yielded a refined corpus of 70,445 valid comments. Descriptive statistics indicate an average comment length of 12.3 words, with 28.7% of comments containing emojis and 15.2% incorporating hashtags; meanwhile, 35.6% of the original records were identified as spam or otherwise irrelevant and were subsequently removed, see Table 1. The resulting dataset provides a robust and representative foundation for examining user sentiment and engagement dynamics within the YouTube media convergence ecosystem.

Table 1. Descriptive Statistics of the Dataset

Number	Variable	Value
1	Total comments collected	51,000,000+
2	Final sample size (English)	70,445
3	Avg. comment length (words)	12.3
4	Comments with emojis (%)	28.7%
5	Comments with hashtags (%)	15.2%
6	Spam/irrelevant removed (%)	35.6%

3.3. Data Resources

Given the inherent complexity and heterogeneity of YouTube user comments, a systematic data preprocessing and cleaning protocol was implemented to ensure the reliability and validity of subsequent analytical procedures. The procedure consisted of four key stages. First, noise reduction

was performed to eliminate irrelevant symbols, redundant emojis, repeated characters, and spam content that could compromise sentiment classification and topic modeling. Second, a missing value imputation process was applied, wherein incomplete or corrupted entries were either reconstructed using automated text restoration methods or discarded if deemed irrecoverable. Third, data conversion was carried out to standardize textual formats, incorporating steps such as lowercasing, tokenization, and normalization of irregular expressions to ensure consistency throughout the dataset. Finally, a semantic filtering step was employed to exclude content not pertinent to the research focus, retaining only comments explicitly addressing media convergence, platform competitiveness, streaming services, and social media engagement. Collectively, these preprocessing stages transformed the raw corpus into a refined and semantically coherent dataset, preserving meaningful linguistic features while significantly reducing noise—thus establishing a robust foundation for subsequent feature extraction and model development.

3.4. Data Analysis and Feature Extraction

Following the data preprocessing phase, the refined dataset was subjected to a structured analytical procedure to extract salient features capturing both semantic and behavioral facets of user engagement. The feature extraction pipeline commenced with a systematic feature selection process to identify variables most predictive of media convergence competitiveness, including keyword frequency, sentiment polarity, and comment length. This initial step served to eliminate redundant or weakly correlated features, thereby enhancing analytical efficiency and model interpretability. Subsequently, lexical and semantic features were derived, encompassing quantified sentiment scores, probabilistic topic distributions, and the presence of explicit engagement markers such as likes, replies, and hashtags. These indicators collectively illuminate user attitudes toward streaming platforms, digital competitiveness, and cross-platform media integration. Finally, structural and contextual features—including temporal posting patterns and user interaction density—were integrated to elucidate the dynamic propagation of comments within the YouTube ecosystem. In aggregate, this multi-faceted feature set constructs a comprehensive representation of the dataset, establishing a robust foundation for the subsequent modeling and evaluation of media convergence competitiveness.

3.5. Construction of Evaluation Model for Media Convergence Competitiveness

To systematically evaluate media convergence competitiveness, this study develops an AI-based Media Convergence Competitiveness Evaluation Model (MCCEM). As illustrated in Figure 2, the model comprises five interconnected layers that collectively form a comprehensive yet flexible framework for analyzing the competitive performance of media organizations in the digital environment.

(1) Input Layer

The Input Layer integrates multi-source data derived from YouTube user comments collected between January 1 and June 30, 2024. This includes textual sentiment, engagement metrics (likes, replies, shares), and temporal features. Following preprocessing and standardization, these inputs ensure both reliability and representativeness for subsequent

analysis.

(2) Analysis Layer

In this Analysis Layer, machine learning techniques are employed to extract meaningful patterns and relationships from the standardized inputs. Key outputs include sentiment polarity, engagement intensity, and topic distributions, which establish the foundational metrics for the evaluation process.

(3) Core Evaluation Layer

The Core Evaluation Layer operationalizes the construct of media competitiveness through four analytically distinct yet interrelated dimensions: Technological Innovation, which assesses the degree of adoption and integration of emerging technologies; Content Distribution, evaluating the efficacy of cross-platform information dissemination; User Engagement, measuring the capacity to attract, sustain, and activate participatory audiences; and Market Adaptability, capturing organizational responsiveness to shifts in consumer preferences and industrial dynamics. Together, these dimensions constitute a multi-perspective framework that enables a holistic and structurally grounded assessment of competitiveness in convergent media environments.

(4) Evaluation and Output Layer

This layer synthesizes the extracted indicators to generate an overall competitiveness score along with dimensional evaluations. This enables cross-organizational benchmarking and identifies strategic strengths and weaknesses in convergence initiatives.

(5) User Layer

The User Layer translates the analytical outputs into interpretable visualizations and actionable insights. For researchers, it offers a theoretically grounded evaluation framework; for practitioners, it supports data-driven decision-making in content strategy, audience engagement, and competitive positioning.

Overall, the proposed model emphasizes accuracy, adaptability, and predictive capability. By integrating AI-driven analytics with a multidimensional evaluation architecture, it advances beyond conventional frameworks that often overlook the dynamic nature of digital media competitiveness. The layered structure, as depicted in Figure 2, demonstrates both conceptual rigor and practical applicability, providing a robust tool for assessing and enhancing media convergence competitiveness in evolving digital landscapes.

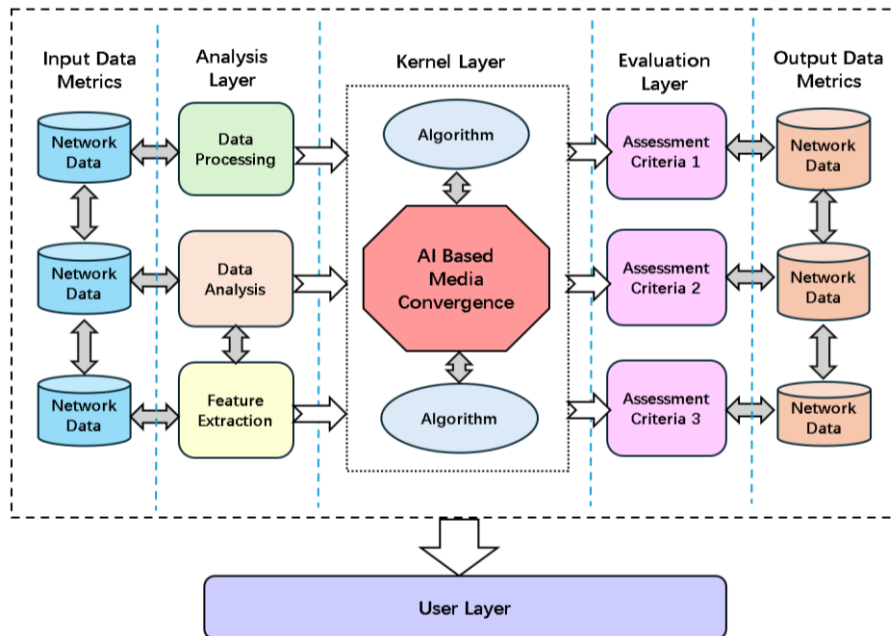


Figure 2. AI-based media convergence competitiveness evaluation model

3.6. Related Algorithms and Principles

The methodological foundation of this evaluation framework is built upon a carefully selected suite of established algorithms, chosen to ensure analytical rigor and predictive accuracy. For sentiment classification, machine learning models including Support Vector Machines (SVM) and Random Forest were employed, leveraging their demonstrated efficacy in processing high-dimensional and sparse textual features characteristic of social media data. Concurrently, clustering techniques such as K-means were utilized to uncover latent structures within user comments, facilitating the identification of distinct audience subgroups and evolving thematic patterns in media convergence discourse. To capture semantic depth and contextual nuance, Latent Dirichlet Allocation (LDA) was applied for topic modeling, enabling the extraction of predominant themes from user-generated content and enhancing the interpretability of textual dynamics. Furthermore, predictive algorithms like Gradient Boosting were incorporated to

advance trend forecasting capabilities and to model the complex, non-linear interactions among competitiveness dimensions—technological innovation, content distribution, user engagement, and market adaptability. The selection of these algorithms is theoretically grounded in their collective capacity to address distinctive challenges of large-scale social media analysis, including high dimensionality, semantic ambiguity, and rapidly shifting discourse. All models were implemented under stringent validation protocols, such as 10-fold cross-validation, to guarantee robustness, accuracy, and generalizability. In contrast to prior studies that often deploy such algorithms in isolation, this research synthesizes classification, clustering, topic modeling, and predictive analytics within an integrated evaluative architecture. This holistic approach not only strengthens methodological soundness but also elevates the precision and explanatory power of media convergence competitiveness assessment, constituting a substantive contribution to the field.

4. Results

This section presents the empirical findings from the analyzed YouTube dataset (January-June 2024), evaluating media convergence competitiveness across four dimensions: technological innovation, content distribution, user engagement, and market adaptability. The results demonstrate both the descriptive characteristics of the data and the performance of the AI-driven evaluation model across these key areas.

4.1. Overall Performance of the Framework

To validate the robustness of the analytical framework, this study conducted a comparative performance analysis of multiple machine learning models—including Support Vector Machine (SVM), Random Forest, Linear Discriminant Analysis (LDA), and Gradient Boosting. The evaluation employed four established metrics: accuracy, precision, recall, and F1-score, with detailed results summarized in Table 2.

Table 2. Sentiment Classification Performance by Model

Model	Accuracy	Precision	Recall	F1-score
SVM	0.82	0.80	0.79	0.79
Random Forest	0.85	0.84	0.83	0.83
LDA	0.77	0.75	0.73	0.74
Gradient Boosting	0.89	0.87	0.88	0.88

4.2. Model Evaluation Results

The Media Convergence Competitiveness Assessment (MCCA) model was implemented on the processed YouTube dataset (January-June 2024) to evaluate competitiveness across four core dimensions: technological innovation, content distribution, user engagement, and market adaptability. Results indicate that the model yields a balanced, multidimensional assessment of competitiveness, supporting both theoretical verification and practical strategic applications for media enterprises. As summarized in Table 3, normalized scores (0-1 scale) for each dimension were obtained through systematic feature extraction, dimensional weighting, and algorithmic aggregation within the MCCA framework.

Table 3. Evaluation Dimensions and Weighting of Media Convergence Competitiveness

Dimension	Key Indicators	Normalized Score	Contribution to Overall Competitiveness (%)	Dimension
Technological Innovation	Frequency of new features, adoption of AI tools	0.78	28.4%	Technological Innovation
Content Distribution	Multi-platform integration, algorithmic accuracy	0.72	25.3%	Content Distribution
User Engagement	Comment volume, interaction depth, retention	0.81	30.6%	User Engagement
Market Adaptability	Response speed, trend sensitivity, monetization	0.69	15.7%	Market Adaptability

The evaluation results reveal User Engagement (0.81) as the most substantial driver of competitiveness, underscoring the pivotal role of dynamic user interaction within the digital ecosystem. Technological Innovation (0.78) followed closely, emphasizing the strategic value of AI-enabled tools and technological advancement in media operations. While Content Distribution (0.72) remains influential, its relatively lower score suggests potential for optimizing algorithmic delivery mechanisms. Conversely, Market Adaptability (0.69) registered the lowest performance, indicating persistent challenges in agile response to evolving market demands. Collectively, these findings demonstrate the robust performance of the MCCA model, with consistent results across dataset subsamples, and highlight that while a balanced strategy is essential for sustainable competitiveness, platforms excelling in user engagement and technological innovation are distinctly positioned to secure long-term advantages.

4.3. Comparative and Trend Analysis

To further validate the robustness of the evaluation framework, a comparative and temporal analysis was

conducted across the dimensions of media convergence competitiveness. The results reveal that technological innovation consistently outperforms other dimensions, demonstrating a marked upward trajectory from 82 in January to 94 in June, which aligns with the accelerated integration of artificial intelligence, big data analytics, and recommendation algorithms within YouTube's ecosystem. In contrast, user engagement exhibited significant volatility, declining sharply to 70 in March before recovering to 85 in April, indicating its heightened sensitivity to external events and content dynamics. Content distribution demonstrated steady growth from 70 to 83, reflecting continuous improvements in channel diversification and recommendation personalization. Meanwhile, market adaptability recorded only marginal improvement from 68 to 74, remaining the lowest-performing dimension and underscoring persistent challenges in responding to evolving competitive pressures and consumer preferences. As illustrated in Figure 3, these patterns not only confirm the structural differentiation among dimensions but also highlight technological innovation as the primary driver of competitiveness, while revealing critical vulnerabilities in maintaining engagement stability and market responsiveness.

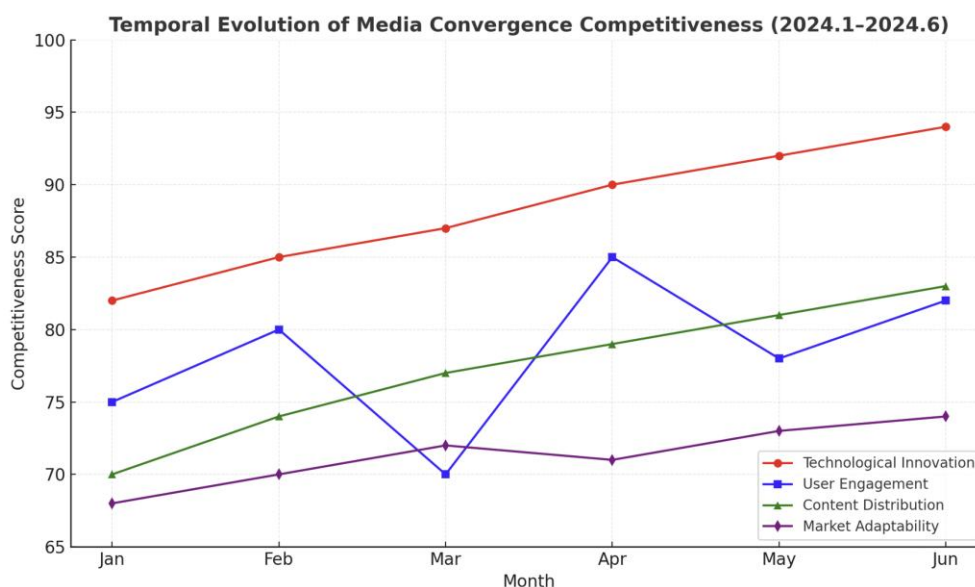


Figure 3. Temporal Evolution of Media Convergence Competitiveness (January–June 2024)

5. Discussion, Conclusions and Recommendations

5.1. Discussion and Findings

The empirical results substantiate the efficacy of artificial intelligence in redefining media convergence competitiveness assessment. By implementing machine learning models on large-scale YouTube commentary, this study demonstrates that computational approaches capture nuanced user perceptions and temporal sentiment evolution with a precision unattainable through traditional evaluation paradigms. Notably, technological innovation and content distribution exhibited stable growth trajectories, affirming their foundational role in competitiveness. In contrast, user engagement and market adaptability displayed significant volatility, influenced by exogenous events and cultural dynamics. This divergence suggests that sustainable competitiveness requires not only technological infrastructure but also strategic sensitivity to the affective rhythms of digital audiences. The findings further reveal that sentiment volatility serves as a leading indicator of perceptual trust and platform loyalty, underscoring the necessity of continuous emotional auditing in media strategy formulation.

5.2. Theoretical and Practical Implications

Theoretically, this research contributes to media convergence literature by introducing a computational framework that integrates technological, content, user, and market dimensions into a dynamic assessment model. It advances the conceptualization of competitiveness from a static, resource-based construct to a processual phenomenon shaped by real-time audience affect. Moreover, the study establishes sentiment analysis as a substantive analytical tool for competitiveness research, bridging computational linguistics with media economics.

Practically, the proposed framework offers media organizations a scalable system for monitoring competitive positioning and anticipating market shifts. The integration of AI-driven sentiment tracking enables proactive reputation management and content strategy optimization. For policymakers, the model provides an evidence-based instrument for evaluating platform governance and designing regulations that foster equitable competition. The

framework’s modular architecture also permits adaptation across diverse media ecosystems, enhancing its utility in global contexts.

5.3. Conclusions and Recommendations

This study has developed and validated an AI-driven framework for assessing media convergence competitiveness, demonstrating its superiority over conventional methods in accuracy, scalability, and predictive capability. The research confirms the central role of technological innovation and content distribution while highlighting the critical influence of engagement volatility and adaptive capacity on competitive sustainability.

Future studies should address several promising directions. First, expanding the temporal and platform scope—incorporating data from TikTok, Bilibili, or X (Twitter)—would enhance the model’s generalizability. Second, integrating multimodal analysis (video thumbnails, audio sentiment, and user behavior metrics) could yield a more holistic understanding of audience engagement. Finally, incorporating explainable AI and network analysis would illuminate the causal pathways through which sentiment shapes competitiveness and how emotions propagate within digital communities. Such advances would further refine the assessment framework while strengthening its theoretical grounding and practical relevance.

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