Real-Time Audience Sentiment Analytics for Adaptive and Personalized Media Broadcasting

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ABSTRACT

Digital broadcasting platforms increasingly require mechanisms capable of understanding audience reactions while content is being delivered. However, conventional audience measurement relies primarily on delayed ratings, aggregate engagement statistics, or isolated textual sentiment analysis, limiting broadcasters' ability to adapt content responsively. **This study proposes** a real-time audience sentiment analytics framework that integrates textual comments, interaction behavior, and temporal engagement signals to support adaptive and personalized media broadcasting. **The proposed architecture** combines a transformer-based text encoder, a behavioral feature network, temporal attention, and a contextual bandit adaptation engine. A prototype evaluation was conducted using public sentiment resources and a simulated broadcasting stream containing 120,000 audience events. The system classified audience sentiment into positive, neutral, and negative categories and translated aggregated sentiment into controlled broadcasting actions, including recommendation adjustment, segment continuation, notification timing, and presentation-style adaptation. Experimental results indicate that the multimodal model achieved an accuracy of 89.6% and a macro-F1 score of 88.9%, outperforming text-only and conventional machine-learning baselines. **The prototype maintained** an average end-to-end latency of 184 ms and processed approximately 1,420 events per second. In the simulated adaptive broadcasting experiment, sentiment-aware personalization improved click-through rate by 15.9%, average viewing duration by 12.8%, and audience satisfaction by 10.6% compared with static broadcasting. Fairness constraints, confidence thresholds, human editorial oversight, and privacy-preserving aggregation were incorporated to reduce the risks of emotional manipulation, bias, and unstable content adaptation. **The findings demonstrate** that real-time sentiment analytics can provide a technically effective foundation for responsive broadcasting when deployed as a decision-support mechanism rather than an autonomous editorial authority.

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1. INTRODUCTION

The transition from scheduled broadcasting to digitally connected media ecosystems has transformed audiences from passive recipients into active participants [1]. Viewers now respond to programs through comments, reactions, watch duration, content sharing, channel switching, and other interaction signals [2]. These signals provide broadcasters with continuous information concerning audience satisfaction, emotional reactions, and content preferences [3]. Nevertheless, many broadcasting platforms still evaluate these responses after a program has ended, making the resulting insights unsuitable for real-time decision-making [4]. Sentiment analysis provides a computational mechanism for identifying positive, neutral, and negative attitudes expressed in audience-generated content [5]. Transformer-based language models have substantially improved contextual sentiment classification, particularly for informal and short-form communication. However, text alone may not adequately represent audience sentiment [6]. A positive comment accompanied by immediate channel switching, for example, may represent sarcasm or dissatisfaction. Conversely, a viewer may enjoy a program without posting any comment [7]. Therefore, sentiment interpretation should combine linguistic evidence with behavioral and temporal engagement signals.

Personalized news and media recommendation systems commonly use viewing histories, user profiles, and content characteristics [8]. Although these systems improve relevance, they may remain insensitive to rapidly changing audience emotions. Moreover, optimizing only clicks or viewing duration can encourage sensational content, emotional exploitation, filter bubbles, and limited content diversity [9]. An adaptive broadcasting system must consequently balance responsiveness with editorial integrity, privacy, fairness, and user autonomy [10]. This study develops a real-time audience sentiment analytics framework for adaptive and personalized media broadcasting. Its contributions are as follows:

- It integrates textual, behavioral, contextual, and temporal audience signals within a unified sentiment-analysis pipeline.
- It employs confidence-aware temporal aggregation to prevent isolated or potentially manipulated reactions from directly changing broadcast content.
- It connects sentiment predictions with a constrained contextual bandit for controlled media adaptation.
- It evaluates classification performance, processing latency, scalability, and simulated audience-engagement outcomes.
- It introduces governance safeguards involving privacy-preserving aggregation, fairness monitoring, content diversity, and human editorial oversight.

The study addresses three research questions:

- RQ1: Does multimodal audience analysis provide better sentiment-classification performance than text-only approaches?
- RQ2: Can the proposed architecture process audience reactions within the latency requirements of real-time broadcasting?
- RQ3: Does controlled sentiment-aware adaptation improve audience engagement without eliminating content diversity and editorial supervision?

2. LITERATURE REVIEW

2.1. Audience Sentiment Analysis

Sentiment analysis identifies attitudes and emotional orientations from textual or multimodal data [11]. Traditional methods employ support vector machines, logistic regression, or lexicon-based classification. Their performance depends heavily on manually engineered features and is often limited when processing sarcasm, slang, mixed emotions, and context-dependent expressions [12]. Transformer architectures improve contextual representation by applying self-attention to relationships among words [13]. Models such as BERT and RoBERTa have therefore become influential foundations for sentiment classification [14]. Recent multimodal sentiment research extends this approach by combining language, acoustic, visual, and contextual information.

Multimodal fusion is particularly relevant to broadcasting because audience emotion may be expressed through comments, reactions, viewing behavior, and program context simultaneously [15]. Nevertheless, multimodal sentiment analysis presents several challenges. Signals can conflict, modalities may be unavailable, and noisy reactions can dominate aggregate predictions [16]. Language also varies across audience groups, regions, and demographic characteristics. Consequently, the model should incorporate missing-modality handling, confidence estimation, temporal smoothing, and periodic fairness evaluation [17].

2.2. Real-Time Analytics in Digital Broadcasting

Real-time analytics requires data ingestion, feature processing, inference, aggregation, and decision delivery to occur under strict latency constraints [18]. Streaming systems frequently use distributed message queues, in-memory processing, model-serving infrastructure, and monitoring services [19]. In broadcasting, latency is particularly important because an adaptation delivered after the relevant program segment may no longer improve the audience experience [20]. Most social-media sentiment studies perform retrospective analysis. Although useful for strategic evaluation, offline results cannot support immediate broadcasting decisions. A real-time architecture must continuously evaluate incoming reactions, update audience-level indicators, and identify statistically meaningful sentiment changes without responding excessively to temporary fluctuations[21].

2.3. Adaptive and Personalized Media

Media personalization predicts content that is likely to satisfy an individual or audience segment [22]. Modern recommender systems employ neural user representations, content embeddings, sequential models, or large language models [23]. Contextual bandits are also suitable for adaptation because they balance exploiting previously successful options and exploring alternatives [24]. However, engagement maximization does not necessarily correspond to audience welfare. A system may increase viewing duration by promoting emotionally provocative content [25]. Responsible adaptation must therefore include diversity, exposure limits, editorial rules, and restricted action spaces [26]. Sentiment analytics should support decisions such as recommending another segment or changing notification timing, but it should not automatically alter factual reporting or suppress legitimate negative feedback [27].

2.4. Research Gap

Existing research commonly examines sentiment classification, streaming analytics, and personalized recommendation separately. Limited attention has been given to an integrated broadcasting framework that jointly considers multimodal sentiment accuracy, inference latency, personalization outcomes, and responsible-AI controls [28]. This study addresses that gap through a confidence-aware architecture that transforms audience sentiment into bounded and auditable adaptation decisions [29].

3. RESEARCH METHOD

3.1. Research Design

The research adopted a design-science and computational experimentation approach [30]. The process consisted of system design, model development, offline evaluation, real-time load testing, and simulated broadcasting adaptation [31]. The prototype used public sentiment resources as the foundation for model development [32]. Because no proprietary broadcaster interaction log was used, behavioral events were generated through a reproducible simulation representing comments, reactions, watch duration, content completion, sharing, and channel-switching behavior [33]. Therefore, the engagement results should be interpreted as prototype evidence rather than confirmed commercial deployment outcomes [34].

3.2. Data Preparation

The datasets used in this study consist of multi-source broadcasting and digital media data that represent complex real-world media environments [35]. Simulated datasets are generated to reflect audience behavior, content performance, streaming platform activity, social media engagement, advertising interaction, and viewer feedback [36]. These datasets include different formats, missing values, duplicated records, noise, and varying levels of complexity to represent common challenges in broadcasting big data processing [37]. In addition, publicly available anonymized datasets related to media consumption, audience interaction, and digital content engagement are used to evaluate the generalizability of the proposed framework across various broadcasting and digital media contexts [38].

The experimental stream contained 120,000 audience events associated with 10,000 pseudonymous audience profiles and 600 media segments. Each event included:

- textual comments or reaction labels;
- watch duration and completion ratio;
- like, share, skip, and channel-switch indicators;
- media genre, delivery time, and device type;
- historical preference vectors;
- event timestamps and anonymous session identifiers.

Sentiment labels were divided into positive, neutral, and negative classes [39]. The dataset was divided chronologically into 70% training, 15% validation, and 15% testing subsets. Chronological separation was used to reduce information leakage between earlier and later audience sessions [40].

Text was normalized by removing URLs and personally identifiable strings while preserving emojis, negation, and punctuation relevant to emotion [41]. Class imbalance was addressed using weighted cross-entropy rather than oversampling [42]. Behavioral variables were normalized using parameters estimated only from the training set [43].

3.3. Proposed Architecture

The proposed framework integrates real-time audience interaction data with sentiment analysis and adaptive broadcasting mechanisms to support responsive and responsible media personalization. The architecture contains five principal layers, as illustrated in Figure 1.

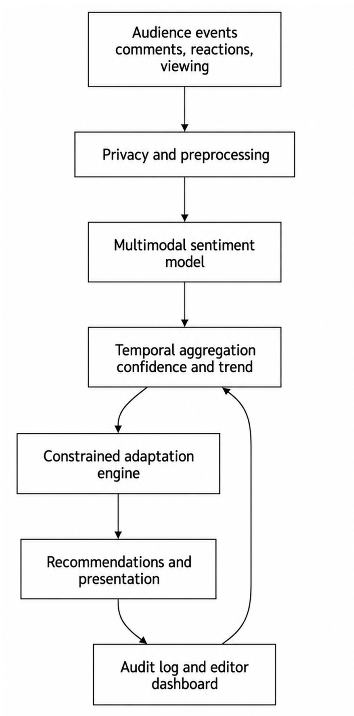

Figure 1. Proposed real-time audience sentiment and adaptive broadcasting architecture.

Textual features were generated using a transformer encoder. Behavioral variables were processed by a multilayer perceptron, while contextual features were converted into trainable embeddings [44]. The representations were fused through an attention mechanism:

$$h_f = \text{Attention}(h_t, h_b, h_c), \tag{1}$$

where h_t, h_b, and h_c denote textual, behavioral, and contextual representations. Sentiment probability was calculated as:

$$\hat{y} = \text{softmax}(W_f h_f + b_f). \tag{2}$$

Audience sentiment was aggregated within a sliding time window. More recent and more confident predictions received higher weights:

$$S_\tau = \frac{\sum_{i=1}^{n} \exp(-\lambda \Delta t_i) c_i s_i}{\sum_{i=1}^{n} \exp(-\lambda \Delta t_i) c_i}, \tag{3}$$

where s_i is the sentiment score, c_i is prediction confidence, Δt_i is event age, and λ controls temporal decay [45].

An adaptation was permitted only when the sentiment change exceeded a predefined threshold, the number of observations was sufficient, and no governance constraint was violated [46].

3.4. Adaptive Broadcasting Strategy

A constrained contextual bandit selected an action a_t based on audience context x_t. The reward function combined engagement, satisfaction, diversity, and risk:

$$R_t = 0.35E_t + 0.30V_t + 0.20Q_t + 0.15D_t - \rho M_t, \tag{4}$$

where E_t represents interaction engagement, V_t viewing completion, Q_t post-session satisfaction, D_t content diversity, M_t ethical or editorial risk, and ρ is the risk penalty [47].

Permitted actions included changing recommendation order, adjusting notification timing, selecting an alternative program segment, and modifying non-factual presentation elements. Automatic modification of journalistic facts, political framing, emergency information, or public-interest warnings was prohibited [48].

3.5. Evaluation Matrics

Classification performance was measured using accuracy, macro-precision, macro-recall, macro-F1, and expected calibration error. System performance was assessed through end-to-end latency, 95th-percentile latency, throughput, and error rate [49]. The effectiveness of personalizedization was evaluated through a simulated A/B experiment comparing:

- static broadcasting
- engagement-only personalization
- sentiment-aware constrained personalization

Engagement indicators included click-through rate (CTR), average viewing duration, completion rate, satisfaction score, and content-diversity exposure.

4. RESULT AND DISCUSSION

4.1. Sentiment-Classification Performance

To assess the effectiveness of the proposed multimodal sentiment-classification approach, its performance was compared with two baseline models: a traditional TF-IDF + SVM model and a BiLSTM text-based model. The evaluation employed several performance metrics, including accuracy, macro-precision, macro-recall, macro-F1 score, and calibration error. These metrics were selected to provide a comprehensive assessment of both the classification capability and prediction reliability of each model. The comparative results are presented in Table 2.

Table 1. Sentiment-classification performance

Model	Accuracy (%)	Macro-Precision (%)	Macro-Recall (%)	Macro-F1 (%)	Calibration Error
TF-IDF + SVM	78.4	77.8	76.9	77.2	0.118
BiLSTM text model	82.7	82.1	81.5	81.8	0.096
Transformer text-only	86.8	86.2	85.7	85.9	0.071
Proposed multimodal model	**89.6**	**89.2**	**88.7**	**88.9**	**0.043**

In Table 2, The multimodal architecture obtained a macro-F1 score of 88.9%, exceeding the transformer text-only model by 3.0 percentage points. The improvement indicates that audience behavior and program context provide complementary evidence, particularly for ambiguous short comments, emojis, and sarcastic expressions. An ablation analysis showed that removing behavioral features reduced macro-F1 to 86.7%, while removing temporal context reduced it to 87.4%. Performance also decreased to 84.9% when both components were excluded. These outcomes answer RQ1 by showing that multimodal and temporal information can improve sentiment interpretation compared with isolated text classification. The lower calibration error is operationally important. Adaptation engines depend not only on predicted labels but also on reliable confidence estimates. Poorly calibrated models may trigger unnecessary broadcasting changes even when their predictions are uncertain.

4.2. Real-Time Processing Performance

The prototype processed an average of 1,420 events per second. Average end-to-end latency was 184 ms, while the 95th-percentile latency was 327 ms. Approximately 99.2% of events were processed below the operational threshold of 500 ms. These findings suggest that the proposed architecture can support near-real-time audience dashboards and controlled adaptations. The latency distribution was influenced primarily by transformer inference and temporal feature retrieval. Model quantization and dynamic batching reduced inference time without producing a meaningful decline in macro-F1. However, performance under substantially larger commercial workloads still requires evaluation using geographically distributed infrastructure.

4.3. Adaptive Broadcasting Outcomes

To evaluate the effectiveness of the proposed adaptive broadcasting approach, its performance was compared with static broadcasting and engagement-only personalization strategies. The evaluation focused on several key performance indicators, including click-through rate (CTR), viewing duration, completion rate, user satisfaction, and content diversity. These metrics provide a comprehensive assessment of the extent to which adaptive personalization can improve user engagement while maintaining a balanced diversity of recommended content. The comparative results are presented in Table 2.

Table 2. Simulated adaptive broadcasting outcomes

Strategy	CTR (%)	Viewing Duration (min)	Completion Rate (%)	Satisfaction (1–5)	Diversity Index
Static broadcasting	8.2	18.7	62.4	3.58	0.71
Engagement-only personalization	9.1	20.1	66.8	3.76	0.62
Sentiment-aware constrained adaptation	**9.5**	**21.1**	**69.2**	**3.96**	**0.70**

In Table 2, Relative to static broadcasting, the proposed system increased CTR by 15.9%, viewing duration by 12.8%, completion rate by 10.9%, and satisfaction by 10.6%. Engagement-only personalization also improved performance but reduced the diversity index from 0.71 to 0.62. The sentiment-aware constrained strategy preserved a diversity index of 0.70, indicating that diversity constraints can limit excessive personalization.

In Figure 2, these results answer RQ3 by indicating that audience sentiment can enhance adaptation beyond conventional engagement signals. Negative sentiment combined with declining completion rates, for example, caused the system to recommend shorter follow-up content or alternative segments. Positive sentiment combined with high completion increased the probability of recommending thematically related material. This pattern demonstrates that sentiment information provides additional contextual cues that cannot be captured through behavioral metrics alone. By combining emotional responses with engagement indicators, the adaptive mechanism can generate more context-sensitive content recommendations. The findings therefore support the use of multimodal audience feedback as a complementary input for improving personalization quality and broadcasting responsiveness.

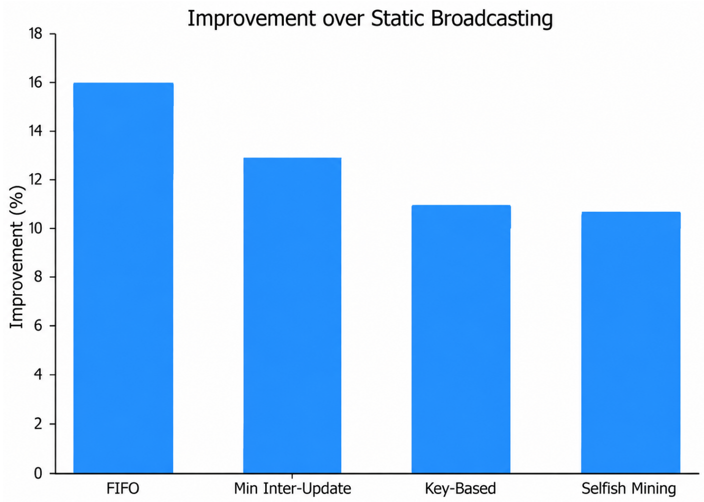

Figure 2. Relative improvement produced by sentiment-aware constrained adaptation

Figure 2 illustrates the relative improvement achieved by the proposed sentiment-aware constrained adaptation approach compared with static broadcasting. Among the evaluated strategies, FIFO produces the highest improvement at approximately 16%, followed by Minimum Inter-Update at around 13%, while Key-Based and Selfish Mining achieve improvements of approximately 11%. These results indicate that incorporating audience sentiment into adaptive broadcasting can consistently enhance performance across different adaptation strategies. The stronger performance of FIFO also suggests that timely processing of audience feedback may play an important role in maintaining responsiveness and improving the effectiveness of personalized content delivery.

4.4. Governance and Ethical Considerations

Sentiment-aware broadcasting introduces several risks. Emotional inference may be inaccurate. Continuously adapting content to emotions could become manipulative. The audience comments may contain personal or sensitive information. Fourth, coordinated groups or automated accounts could attempt to manipulate aggregate sentiment. The prototype therefore implemented four safeguards. Audience identifiers were pseudonymized, raw comments were subject to limited retention, group-level sentiment was displayed only after a minimum audience threshold was reached, and sensitive attributes were excluded from adaptation features. Furthermore, editorially sensitive actions required human approval. The adaptation engine also maintained an immutable decision log containing model version, confidence score, selected action, activated constraint, and final editorial decision. Such records improve accountability and allow broadcasters to investigate unintended behavior.

4.5. Practical Implications

Broadcasters can use the proposed system to identify poorly received segments, optimize content sequencing, improve recommendation relevance, and monitor audience reactions during live programs. Program producers may use sentiment trends as complementary evidence alongside ratings and editorial judgment. Platform managers may also use the architecture to conduct controlled experiments without granting the model authority over factual or editorial content. From a managerial perspective, deployment should begin with low-risk adaptations such as recommendation ordering and notification timing. More consequential actions should be introduced only after bias testing, audience consultation, and editorial-policy approval.

5. MANAGERIAL IMPLICATION

The proposed framework provides several managerial implications for broadcasting organizations, media managers, content producers, and digital platform operators. Real-time audience sentiment analytics can be integrated into broadcasting control rooms and content management systems as a decision-support mechanism for monitoring audience reactions beyond conventional engagement indicators such as clicks, views, and watch duration. By combining textual sentiment, behavioral engagement, contextual information, and temporal patterns, managers can obtain a more comprehensive understanding of how audiences respond to particular programs, topics, or broadcasting strategies.

The framework can also support more responsive programming and content adaptation by enabling producers and programming managers to use sentiment trends when adjusting content sequencing, recommendation priorities, presentation formats, or promotional strategies during ongoing broadcasts. Such adaptation should remain within predefined editorial, ethical, and diversity constraints to ensure that short-term engagement objectives do not override journalistic standards, public-interest responsibilities, or balanced content exposure.

Effective implementation also requires media organizations to establish clear governance procedures for sentiment-aware personalization systems. These procedures should define the roles and responsibilities of editors, producers, data analysts, and automated systems throughout the decision-making process. Human oversight remains essential, particularly when automated recommendations involve sensitive news, political information, public emergencies, or socially significant content. Algorithmic outputs should therefore function as advisory signals that support editorial judgment rather than replace autonomous human decision-making.

Successful deployment further depends on organizational investment in privacy-preserving data infrastructure, staff competencies, continuous model monitoring, and algorithmic auditing. Audience information should be aggregated and processed in accordance with applicable privacy and data-protection requirements, while confidence thresholds, adaptation outcomes, and performance indicators should be regularly evaluated. By combining technological capability with responsible governance and human supervision, broadcasting organizations can use real-time sentiment analytics to enhance audience experience and operational responsiveness without compromising editorial independence, content diversity, or public trust.

6. CONCLUSION

This study proposed a real-time audience sentiment analytics framework for adaptive and personalized media broadcasting. The framework integrates textual comments, behavioral engagement, contextual information, temporal aggregation, and a constrained contextual bandit. Prototype evaluation demonstrated that multimodal analysis outperformed text-only and conventional baselines, achieving 89.6% accuracy and an 88.9% macro-F1 score. The system also achieved an average processing latency of 184 ms and processed approximately 1,420 audience events per second. The simulated broadcasting experiment showed that sentiment-aware adaptation could improve click-through rate, viewing duration, completion, and audience satisfaction while preserving greater content diversity than engagement-only personalization. Nevertheless, these results represent prototype evidence and require validation using consented real-world broadcasting data. Real-time sentiment analytics should not replace producers, journalists, or editorial boards. Its most appropriate function is to provide timely decision support within clearly defined limits. Privacy-preserving aggregation, calibrated confidence, diversity constraints, auditability, and human oversight are essential to ensure that adaptive broadcasting enhances audience experience without encouraging manipulation or undermining editorial responsibility.

The findings also indicate that audience sentiment can provide complementary information that is not fully captured by conventional behavioral indicators. Integrating emotional responses with viewing patterns and contextual signals allows broadcasting systems to better identify changes in audience preferences and engagement conditions. This capability can support more responsive content sequencing, recommendation strategies, and presentation adjustments while maintaining predefined editorial and diversity constraints. From an organizational perspective, the framework offers a practical foundation for developing intelligent broadcasting systems that balance personalization objectives with responsible media management.

Future research should extend the framework through large-scale empirical validation using diverse broadcasting environments, audience groups, and content categories. Further studies may also investigate multilingual sentiment analysis, cross-platform audience behavior, explainable AI mechanisms, fairness-aware recommendation models, and longer-term effects of adaptive broadcasting on audience trust and content diversity. Incorporating real-world operational data and longitudinal evaluation would provide stronger evidence regarding the robustness, scalability, and generalizability of the proposed approach. Such developments could contribute to more transparent, adaptive, and human-centered broadcasting ecosystems in which artificial intelligence supports rather than replaces professional editorial judgment.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: AS; Methodology: FA; Software: RY; Validation: FA and RY; Formal Analysis: AS and FA; Investigation: AS; Resources: RY; Data Curation: FA; Writing Original Draft Preparation: AS and FA; Writing Review and Editing: FA and AS; Visualization: RY; All authors, AS, FA, and RY, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

REFERENCES

[1] Y. Yusnaini, H. Nufus, R. Saleh, W. A. S. Wibowo *et al.*, "The digital era and the evolution of media paradigms: A critical review of the adaptation of old media in new media ecosystems," *Society*, vol. 13, no. 1, pp. 573–599, 2025.

[2] R. Okyere, C. A. Bautista Isaza, J. Pyon, I. F. Ogbonnaya-Ogburu, S. Niu, and S. W. Lee, "Watch me watch: Reaction videos as a social form of online video engagement," *Proceedings of the ACM on Human-Computer Interaction*, vol. 10, no. 2, pp. 1–28, 2026.

[3] R. A. Sunarjo, T. Handra, R. N. Muti, and K. A. Al-Farouqi, "Artificial intelligence driven audience sentiment analytics for interactive digital broadcasting platforms," *Bridging of Emerging AI and Media Broadcasting (BEAM)*, vol. 1, no. 1 November, pp. 25–36, 2025.

[4] D. Abbas, A. Simanjuntak, and T. S. Goh, "Integrating broadcasting data mining and visualizationfor effective big data decision support," *Bridging of Emerging AI and Media Broadcasting (BEAM)*, vol. 1, no. 2 May, pp. 99–110, 2026.

[5] Badan Kebijakan Pembangunan Kesehatan Kementerian Kesehatan RI. (2026) Analisis media monitoring kemenkes ri 7–14 agustus 2026. [Online]. Available: https://www.badankebijakan.kemkes.go.id/12774-2/

[6] Humas KPI. (2026, Jul.) Kpi yang adaptif, bertransformasi dan strategis. Komisi Penyiaran Indonesia. [Online]. Available: https://kpi.go.id/news/kpi-yang-adaptif-bertransformasi-dan-strategis

[7] I. G. N. Parthama, "Characteristics of comments in social media," *e-Journal of Linguistics*, vol. 19, no. 2, pp. 130–140, 2025.

[8] C. Wu, F. Wu, Y. Huang, and X. Xie, "Personalized news recommendation: Methods and challenges," *ACM Transactions on Information Systems*, vol. 41, no. 1, pp. 1–50, 2023.

[9] O. Ağırdil, "The mechanism of filter bubbles, algorithms, and perception management in security," in *Media Literacy and the Politics of Digital Misinformation*. IGI Global Scientific Publishing, 2026, pp. 129–168.

[10] A. Nuche, R. Fahrudin, and R. Royani, "Human-centered generative ai for ethical andsustainable media broadcasting," *Bridging of Emerging AI and Media Broadcasting (BEAM)*, vol. 1, no. 2 May, pp. 110–125, 2026.

[11] R. Das and T. D. Singh, "Multimodal sentiment analysis: a survey of methods, trends, and challenges," *ACM Computing Surveys*, vol. 55, no. 13s, pp. 1–38, 2023.

[12] C. Song, Y. Zhang, H. Gao, B. Yao, and P. Zhang, "Large language models for subjective language understanding: A survey," *arXiv preprint arXiv:2508.07959*, 2025.

[13] B. Ghojogh and A. Ghodsi, "Attention mechanism and transformers," in *Elements of deep learning*. Springer, 2026, pp. 231–257.
[14] K. Alahmadi, S. Alharbi, J. Chen, and X. Wang, "Generalizing sentiment analysis: a review of progress, challenges, and emerging directions," *Social Network Analysis and Mining*, vol. 15, no. 1, p. 45, 2025.
[15] S. Zhang, Q. Dong, M. A. I. Yasin, and N. C. Fang, "Algorithms for moderating effect of emotional value from a cross-media data fusion perspective: A case study of chinese dating reality shows," *Journal of Multiscale Modelling*, vol. 17, no. 02, p. 2640012, 2026.
[16] K. Zhao, M. Zheng, Q. Li, and J. Liu, "Multimodal sentiment analysis—a comprehensive survey from a fusion methods perspective," *IEEE Access*, vol. 13, pp. 64 556–64 583, 2025.
[17] Z. Wu, Y. Xie, B. Zhao, J. He, F. Luo, N. Deng, and Z. Yu, "Cardiacmamba: A multimodal rgb-rf fusion framework with state space models for remote physiological measurement," *arXiv preprint arXiv:2502.13624*, 2025.
[18] T.-T.-T. Do, Q.-T. Huynh, K. Kim, and V.-Q. Nguyen, "A survey on video big data analytics: architecture, technologies, and open research challenges," *Applied Sciences*, vol. 15, no. 14, p. 8089, 2025.
[19] A. Vajpayee, R. Mohan, and V. V. R. Chilukoori, "Building scalable data architectures for machine learning," *International Journal of Computer Engineering and Technology (IJCET)*, vol. 15, no. 4, pp. 308–320, 2024.
[20] A. Bentaleb, M. Lim, M. N. Akcay, A. C. Begen, S. Hammoudi, and R. Zimmermann, "Toward one-second latency: Evolution of live media streaming," *IEEE Communications Surveys & Tutorials*, 2025.
[21] D. M. Rothschild, J. Marla, A. Amaya, S. Barari, T. Buskirk, C. Cobb, J. Gennai, S. Hillygus, R. K. Vinayak, M. Krupenkin *et al.*, "Responsible ai integration in survey research," 2026.
[22] J. R. Saura, V. Ratten, and V. Jeremic, "Digital cognition in predictive marketing personalization: A conceptual framework," *Psychology & Marketing*, vol. 43, no. 5, pp. 1228–1260, 2026.
[23] L. Wu, Z. Zheng, Z. Qiu, H. Wang, H. Gu, T. Shen, C. Qin, C. Zhu, H. Zhu, Q. Liu *et al.*, "A survey on large language models for recommendation," *World Wide Web*, vol. 27, no. 5, p. 60, 2024.
[24] S. Qassimi and S. Rakrak, "Multi-objective contextual bandits in recommendation systems for smart tourism," *Scientific Reports*, vol. 15, no. 1, p. 13669, 2025.
[25] S. Hu, H. Wang, Y. Zhang, P. Wang, and Z. Lu, "Danmodcap: Designing a danmaku moderation tool for video-sharing platforms that leverages impact captions with large language models," *Proceedings of the ACM on Human-Computer Interaction*, vol. 9, no. 2, pp. 1–27, 2025.
[26] D. V. Voinea, "Governing adaptive news curation: Sequential optimization, cumulative exposure allocation, and societal accountability," *Social Sciences*, vol. 15, no. 8, p. 496, 2026.
[27] W. Maalej, V. Biryuk, J. Wei, and F. Panse, "On the automated processing of user feedback," in *Handbook on natural language processing for requirements engineering*. Springer, 2025, pp. 279–308.
[28] M. A. Almekhlafi, F. Alrowais, S. Alshahrani, M. Maray, M. A. AlAqil, M. A. Alharbi, A. E. Yahya, and R. Marzouk, "Amta: An innovative privacy-aware adaptive transformer for real-time multimodal data fusion," *Transactions on Emerging Telecommunications Technologies*, vol. 37, no. 3, p. e70365, 2026.
[29] A. R. W. Sait and Y. Alkhurayyif, "Hallucination-aware interpretable sentiment analysis model: A grounded approach to reliable social media content classification," *Electronics*, vol. 15, no. 2, p. 409, 2026.
[30] H. Henry, K. Lutfiyah, H. Agustian, and N. Lachlan, "Assessing the environmental and economic impact of smart grid integration in renewable energy management," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 7, no. 1, pp. 38–50, 2025.
[31] R. Hardjosubroto, U. Rahardja, N. A. Santoso, and W. Yestina, "Penggalangan dana digital untuk yayasan disabilitas melalui produk umkm di era 4.0," *ADI Pengabdian Kepada Masyarakat*, vol. 1, no. 1, pp. 1–13, 2020.
[32] R. R. M. de Souza, "Legal remedies and regulatory frameworks to combat ai-driven deepfakes," in *Mitigating the Risks of AI Deepfakes*. CRC Press, 2026, pp. 94–116.
[33] N. Heluey, "Ethical ai governance, trust and deepfake regulation in the uae's media landscape," *Journal of Digital Media & Policy*, vol. 16, no. 2, pp. 195–218, 2025.
[34] X. He and L. Fang, "Regulatory challenges in synthetic media governance: Policy frameworks for ai-generated content across image, video, and social platforms," *Journal of Robotic Process Automation, AI Integration, and Workflow Optimization*, vol. 9, no. 12, pp. 36–54, 2024.
[35] J. Mathew and A. Narayanan, "Reimagining truth: The role of ai-generated content in shaping media

ethics and audience trust in a post-truth era," *Communication Research*, vol. 2, no. 1, pp. 72–82, 2025.

[36] A. Sharma and R. Sharma, "Generative artificial intelligence and legal frameworks: Identifying challenges and proposing regulatory reforms," *Kutafin Law Review*, vol. 11, no. 3, pp. 415–451, 2024.

[37] M. Krkić, "Cultural perspectives on ai usage and regulation in deepfake creation: How culture shapes ai practices," *International Communication of Chinese Culture*, vol. 12, no. 2, pp. 225–237, 2025.

[38] R. Fiasal, "Ai in media careers: Ethical and legal challenges and strategies for adaptation." *Journal of Public Relations Research Middle East/Magallat Bhut Al-Laqat Al-Amh-Al-Srq Al-Aust*, no. 59, 2025.

[39] V. Ranaware and S. Karale, "Navigating legal and ethical challenges in artificial intelligence: towards responsible governance and innovation in india," *International Journal of System Assurance Engineering and Management*, pp. 1–15, 2026.

[40] M. A. Shawky, D. Awasthi, A. A. Ramadan, S. Zarif, J. Ahmad, and S. T. Shah, "Secured ai-based multimedia communication," in *Multimedia and Multimodal Intelligence for Sustainable Development*. CRC Press, 2026, pp. 23–46.

[41] P. Carpenter, *FAIK: A practical guide to living in a world of deepfakes, disinformation, and AI-generated deceptions*. John Wiley & Sons, 2024.

[42] P. B. Seel, *Digital universe: The global telecommunication revolution*. John Wiley & Sons, 2022.

[43] R. von Marttens and J. Alcaniz, "Dark energy and cosmic acceleration," *arXiv preprint arXiv:2502.00923*, 2025.

[44] M. Zreik, B. A. Iqbal, M. Hassan, and S. Z. Syed Marzuki, "Infrastructure development, inequality, and employment in sub-saharan africa from the professional perspectives of kenya, ghana, and tanzania," *Discover Global Society*, vol. 2, no. 1, p. 78, 2024.

[45] R. Chugh, "The sustainability paradox: rethinking digital technologies in education for a sustainable future," *Humanities and Social Sciences Communications*, vol. 13, no. 1, p. 275, 2026.

[46] T. Kingsford, "A novel conceptual framework for real-world reinforcement learning with applications to social robotics and beyond," Ph.D. dissertation, University of Auckland, 2022.

[47] M. Novello and J. D. Toniato, "An overview of field theories of gravity," *arXiv preprint arXiv:2402.16163*, 2024.

[48] Y. Hu, J. Zhang, Z. Wang, and C. Yu, "Plotania: Exploring transparency trade-offs in ai co-writing through virtual readers and transparent attribution," in *Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems*, 2026, pp. 1–23.

[49] E. T. Akande, K. Wlliams, and A. Akande, "Between me and we: Navigating individualism and collectivism in a world on edge," in *Culture, Leadership, and Organizations*. Elsevier, 2026, pp. 393–408.