Artificial Intelligence Driven Audience Sentiment Analytics for Interactive Digital Broadcasting Platforms

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ABSTRACT

The rapid growth of interactive digital broadcasting platforms has significantly transformed the way audiences engage with media content through live chats, comments, and social media interactions. However, the massive volume of user-generated feedback creates challenges for broadcasters in understanding audience sentiment efficiently. **This study aims to analyze** audience sentiment using Artificial Intelligence (AI) driven analytics to improve the understanding of audience engagement in interactive digital broadcasting platforms. **The research** applies a quantitative approach using AI based Natural Language Processing (NLP) techniques to process and analyze audience feedback data collected from comments, live chat interactions, and social media responses related to digital broadcast content. The analytical process includes data preprocessing, sentiment classification, and machine learning based modeling to identify patterns of audience emotional responses and engagement. **The findings** indicate that AI driven sentiment analytics can effectively classify audience opinions and detect real time sentiment trends associated with broadcasted content. The results also demonstrate that AI-based analysis enables broadcasters to gain deeper insights into audience preferences, evaluate content performance, and optimize broadcasting strategies more efficiently compared with conventional manual analysis methods. **In conclusion**, the integration of AI in audience sentiment analytics offers a valuable approach for enhancing audience understanding and supporting data-driven decision-making in modern digital broadcasting ecosystems while promoting more responsive and personalized media experiences.

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1. INTRODUCTION

The rapid advancement of digital technology has significantly transformed the broadcasting industry, shifting traditional media toward interactive digital broadcasting platforms. Modern audiences no longer act solely as passive viewers but actively participate through live chats, comments, and social media interactions [1]. This transformation generates vast amounts of audience feedback data that can provide valuable insights into public perception and engagement. However, analyzing such large-scale user-generated data remains a challenge when relying on conventional analytical methods. Consequently, the integration of AI, particularly sentiment analytics, has emerged as a promising approach to automatically interpret audience opinions and emotional responses in real time within digital broadcasting environments [2].

AI driven sentiment analytics enables broadcasters to extract meaningful patterns from audience interactions using technologies such as NLP and machine learning. These technologies allow media organizations to better understand audience engagement, evaluate content performance, and design more responsive broadcasting strategies [3]. Furthermore, the implementation of AI in media analytics aligns with global sustainability initiatives, particularly the Sustainable Development Goals (SDGs). In the context of digital media transformation, AI-based broadcasting analytics contributes to SDG 9 (Industry, Innovation and Infrastructure) by fostering technological innovation and digital infrastructure development, and SDG 16 (Peace, Justice and Strong Institutions) by supporting transparent, responsible, and data-driven information ecosystems.

Figure 1. AI Broadcasting and SDGs

Figure 1 illustrates the conceptual relationship between AI driven sentiment analytics and relevant SDGs. The integration of AI technologies within digital broadcasting platforms enhances data-driven media innovation and strengthens digital infrastructure, contributing to SDG 9. At the same time, the ability to analyze audience sentiment in real time supports responsible information dissemination, improved transparency, and more responsive communication between broadcasters and audiences, which aligns with the principles of SDG 16. This conceptual linkage highlights how technological advancement in media analytics can simultaneously support sustainable and ethical digital communication ecosystems.

Based on these developments, this study investigates the implementation of AI driven audience sentiment analytics in interactive digital broadcasting platforms [4, 5]. The research aims to explore how AI-based analytical methods can effectively interpret audience feedback and generate insights that support content optimization and audience engagement strategies. By leveraging machine learning and NLP techniques, this study contributes to the growing body of research on intelligent media analytics while highlighting the role of AI technologies in advancing innovative, sustainable, and audience-centered digital broadcasting systems.

2. LITERATURE REVIEW

The literature review presents key theoretical and empirical foundations on AI, sentiment analysis, and audience engagement in digital broadcasting platforms. It highlights prior studies on the use of AI, particularly NLP and machine learning, to analyze audience-generated data and understand audience perceptions, emotional responses, and participation [6]. Overall, this section provides a conceptual basis for the integration of AI-driven analytics in modern broadcasting ecosystems.

2.1. AI in Digital Broadcasting

The integration of AI has significantly transformed the digital broadcasting industry by enabling automated data processing, intelligent content recommendation, and real-time audience interaction analysis. AI technologies such as machine learning and deep learning allow broadcasters to process large volumes of audience-generated data efficiently [7]. These technologies support broadcasting organizations in optimizing content delivery, predicting viewer preferences, and improving the overall broadcasting experience.

Furthermore, AI-driven systems have introduced new capabilities in digital media ecosystems, including automated news production, intelligent media monitoring, and algorithmic content distribution [8]. The use of AI technologies enables broadcasting platforms to become more adaptive and data-driven, allowing media organizations to respond quickly to audience behavior and market trends. Consequently, AI plays a crucial role in shaping the future of interactive and personalized broadcasting services [9].

2.2. Audience Sentiment Analysis Using NLP

Audience sentiment analysis has emerged as a powerful analytical approach for understanding audience perceptions and emotional responses toward media content [10]. By utilizing NLP techniques, large volumes of textual data such as comments, reviews, and social media posts can be systematically analyzed to identify patterns of positive, negative, or neutral sentiments. These insights help broadcasters evaluate audience reactions and refine content strategies to better align with viewer expectations.

Recent studies have demonstrated that NLP-based sentiment analytics can significantly improve the efficiency and accuracy of audience feedback interpretation compared with traditional manual evaluation methods [11]. Through techniques such as text classification, opinion mining, and sentiment detection, broadcasters can gain deeper insights into audience engagement patterns and identify emerging public opinions surrounding broadcast content.

Table 1. Comparison of Sentiment Analysis Techniques in Media Analytics

Technique	**Method Approach**	**Advantages**	**Limitations**	**Application in Media Analytics**
Lexicon-Based Analysis	Uses predefined sentiment dictionaries to classify positive, negative, or neutral words	Simple to implement, does not require large training data	Limited contextual understanding, difficulty detecting sarcasm	Basic audience opinion analysis from comments and reviews
Machine Learning-Based Analysis	Uses supervised learning algorithms such as Naïve Bayes, SVM, or Decision Trees	Higher accuracy than lexicon methods, adaptable to different datasets	Requires labeled training data and feature engineering	Audience sentiment classification from social media interactions
Deep Learning-Based Analysis	Utilizes neural networks such as LSTM, CNN, or Transformer models	Captures complex linguistic patterns and contextual meanings	Computationally intensive and requires large datasets	Advanced sentiment detection in large-scale broadcasting data
Hybrid Approach	Combines lexicon-based methods with machine learning or deep learning techniques	Improved accuracy and contextual understanding	More complex implementation	Real-time sentiment monitoring in digital broadcasting platforms

Table 1 presents a comparison of several commonly used sentiment analysis techniques in media analytics, including lexicon-based methods, machine learning approaches, deep learning models, and hybrid techniques. Each method offers different advantages and limitations in analyzing audience sentiment from textual data such as comments, reviews, and social media interactions [12]. Lexicon-based approaches are relatively simple to implement but often struggle to capture contextual meaning, while machine learning methods provide higher classification accuracy through trained models. Deep learning techniques further enhance sentiment detection by capturing complex linguistic patterns and contextual relationships within large datasets [13]. Meanwhile, hybrid approaches combine multiple techniques to improve analytical performance and reliability. Overall, the comparison highlights the evolution of sentiment analysis methods and emphasizes the growing importance of advanced AI-driven techniques for analyzing large-scale audience feedback in modern digital broadcasting environments.

2.3. Interactive Digital Broadcasting and Audience Engagement

Interactive digital broadcasting platforms have redefined the relationship between media producers and audiences by enabling real-time communication and participation [14]. Features such as live streaming comments, viewer polls, and social media integration allow audiences to actively contribute to the broadcasting experience. This interactive environment creates new opportunities for broadcasters to gather valuable audience insights and enhance content engagement.

The analysis of audience interaction data provides broadcasters with a deeper understanding of audience behavior, preferences, and engagement dynamics [15]. By leveraging interactive analytics, media organizations can evaluate audience responses to broadcast content and develop strategies to increase viewer satisfaction and loyalty. Therefore, integrating audience engagement analytics within digital broadcasting platforms has become a key component in modern media innovation.

Figure 2. Audience Engagement Model

Figure 2 illustrates a dynamic model of audience engagement in interactive broadcasting platforms, highlighting the key components that drive real-time viewer interaction. The model emphasizes how features such as live chat, comments, viewer polls, and social media integration collectively generate valuable audience insights [16]. These insights are then leveraged to optimize content delivery, improve engagement strategies, and enhance overall viewer satisfaction. By visually representing the flow from interactive participation to actionable analytics, the figure demonstrates how broadcasters can utilize AI-driven and data-informed approaches to foster more responsive, personalized, and engaging digital media experiences.

2.4. AI Driven Broadcasting Analytics and Sustainable Media Development

AI driven broadcasting analytics plays an increasingly important role in supporting sustainable and responsible media ecosystems. By leveraging advanced data analytics capabilities, broadcasters are able to systematically monitor audience feedback, detect emerging patterns of misinformation, and ensure that information dissemination remains transparent, accurate, and accountable [17]. These capabilities enable media organizations to move beyond traditional reactive approaches toward more proactive and data-driven decision-making processes. As a result, AI-driven analytics not only improves operational efficiency but also strengthens the integrity and credibility of digital media platforms, contributing to the development of more ethical, adaptive, and audience-centered media environments.

Additionally, the implementation of AI-based analytics aligns closely with global sustainability initiatives, particularly the SDGs. Technologies that facilitate responsible information dissemination, foster digital innovation, and enhance communication infrastructures play a crucial role in advancing sustainable media development. In this context, AI-driven broadcasting analytics supports the creation of more inclusive and resilient digital ecosystems by enabling better access to information and improving the quality of public communication. Consequently, the integration of AI in broadcasting analytics not only enhances media performance but also contributes to broader societal objectives related to digital transformation, transparency, and the development of sustainable and responsible communication systems [18, 19].

3. RESEARCH METHOD

The research methodology employed to investigate audience sentiment and engagement in interactive digital broadcasting platforms is outlined by describing the overall research design, data collection procedures, and analytical techniques used to process audience-generated data [20]. The approach emphasizes the application of AI, particularly NLP and machine learning, to ensure systematic, accurate, and data-driven analysis of audience interactions.

3.1. Research Design

This study employs a quantitative research design to investigate audience sentiment and engagement on interactive digital broadcasting platforms [21]. The design focuses on collecting large-scale user-generated data, including comments, live chat messages, and social media responses, to understand patterns of audience interaction and emotional responses. The research emphasizes the integration of AI techniques, particularly NLP and machine learning, to process and analyze these data efficiently.

The research design also incorporates a cross sectional approach, analyzing audience feedback over multiple broadcasting sessions to identify trends and engagement patterns [22]. This approach allows for both real-time and post event analytics, providing comprehensive insights into audience sentiment and interaction dynamics across different content types.

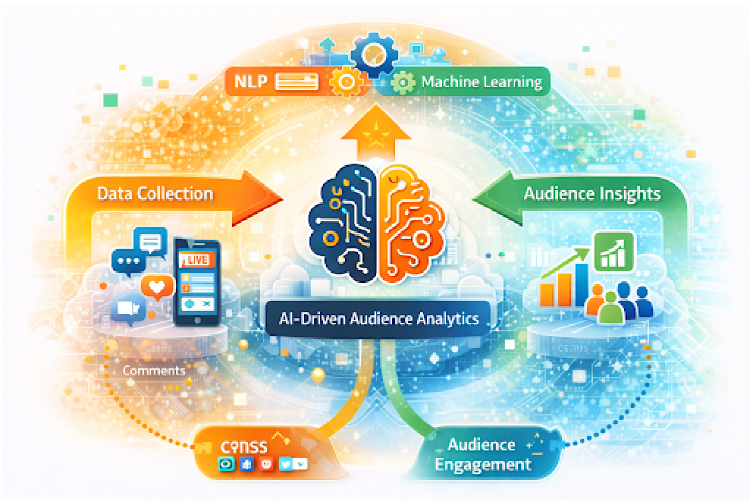

Figure 3. Conceptual Framework of AI-Driven Audience Analytics

Figure 3 presents a conceptual framework of AI-driven audience analytics for interactive digital broadcasting platforms, visually demonstrating the flow from audience data collection to actionable insights. Audience-generated inputs such as comments, live chats, and social media interactions are collected and processed through AI modules, including NLP and machine learning techniques. These processes enable broadcasters to extract sentiment patterns, measure engagement, and generate audience insights that inform content optimization and strategy development [23]. The figure highlights the dynamic interaction between data collection, AI analytics, and audience engagement, emphasizing how AI technologies facilitate real-time, data-driven decision-making and enhance personalized, responsive broadcasting experiences.

3.2. Data Collection

Data for this study are collected from interactive digital broadcasting platforms, including live streaming sessions, program comments, and integrated social media interactions. The dataset encompasses multiple broadcasting events across different content categories to ensure representativeness and reliability in capturing diverse audience sentiment patterns [24]. In addition to textual data, metadata such as timestamps, user IDs, frequency of interaction, and engagement metrics including likes, shares, and comments are also collected to support a more comprehensive analysis of audience behavior. This multi-source data collection approach enables the identification of temporal trends, interaction dynamics, and variations in audience responses across different types of broadcast content, thereby strengthening the robustness of the sentiment analysis [25].

To maintain data quality and ethical standards, several preprocessing and governance measures are implemented throughout the data collection process. All user data are anonymized to remove personally identifiable information, and only publicly available interactions are included to ensure compliance with ethical research practices [26]. The data collection procedure adheres to applicable digital privacy regulations and platform policies, ensuring that participants' identities remain protected. Furthermore, data cleaning techniques such as noise removal, duplicate filtering, and text normalization are applied to improve data accuracy and consistency. These measures collectively ensure that the dataset is reliable, ethically sourced, and suitable for robust statistical and AI-driven analysis.

3.3. Data Analysis

The collected data are processed using NLP techniques, including text preprocessing, tokenization, and sentiment classification. Sentiment analysis is performed using a combination of lexicon-based methods and machine learning algorithms to identify positive, negative, and neutral reactions [27]. Advanced deep learning models, such as LSTM or Transformer-based networks, are applied to capture contextual and semantic nuances in audience feedback.

Additionally, engagement metrics are analyzed to explore correlations between sentiment trends and interaction patterns. This combined AI-driven approach enables real-time and post-event insights, supporting actionable recommendations for content optimization and audience engagement strategies.

Table 2. Sentiment Analysis Techniques and Model Parameters

Technique	**Model / Algorithm**	**Key Parameters**	**Advantages**	**Application in Media Analytics**
Lexicon-Based	Dictionary-Based Sentiment Scoring	Sentiment word list, polarity scores	Simple implementation, no training data required	Basic sentiment classification of comments or social media posts
Machine Learning	Naïve Bayes, SVM, Random Forest	Training dataset size, feature extraction (TF-IDF, n-grams)	High accuracy for structured data, adaptable to datasets	Audience opinion classification and trend detection
Deep Learning	LSTM, CNN, Transformer (BERT, RoBERTa)	Learning rate, epochs, batch size, embedding dimension	Captures contextual and semantic meaning, handles large datasets	Advanced sentiment detection and real-time analysis of live audience feedback
Hybrid Approach	Combination of Lexicon + ML/DL	Sentiment lexicons, model hyperparameters, training dataset	Improved accuracy, better contextual understanding	Real-time sentiment monitoring for interactive digital broadcasting platforms

Table 2 provides a comparison of sentiment analysis techniques and their respective model parameters, highlighting lexicon-based, machine learning, deep learning, and hybrid approaches. Each method offers distinct advantages, from simple implementation in lexicon-based analysis to advanced contextual understanding in deep learning models [28]. The table also outlines key parameters that influence model performance, such as training dataset size, hyperparameters, and embedding dimensions. By presenting applications in media analytics, the table emphasizes how these techniques are utilized to classify audience sentiment, detect engagement trends, and support real-time analysis in interactive digital broadcasting platforms [29, 30].

4. RESULT AND DISCUSSION

The results of the analysis are presented and discussed to highlight the key findings derived from the implementation of AI-driven sentiment analytics on audience interaction data [31]. The discussion focuses on identifying sentiment patterns, evaluating audience engagement, and interpreting how these insights contribute to understanding audience behavior and optimizing digital broadcasting strategies.

4.1. Sentiment Analysis Outcomes

The AI-driven sentiment analysis of audience interactions reveals significant patterns in viewer responses to digital broadcasting content. Positive sentiments tend to dominate live interactions during entertainment programs, while news-related content generates a higher proportion of neutral or mixed reactions. Advanced deep learning models, particularly Transformer-based architectures, demonstrate superior performance in capturing nuanced emotional expressions compared to lexicon-based and traditional machine learning approaches [32, 33]. These findings indicate that AI techniques are highly effective in processing large scale audience feedback and generating accurate, real-time insights into evolving emotional trends within digital broadcasting environments.

Furthermore, the analysis identifies a strong relationship between sentiment patterns and audience engagement metrics, including comment frequency and social media sharing behavior. Content that evokes stronger emotional responses is more likely to stimulate higher levels of audience participation and interaction [34]. This highlights the strategic importance of leveraging AI-driven sentiment analytics to support content optimization and audience engagement planning. By integrating these analytical insights, digital broadcasters can enhance content relevance, improve viewer satisfaction, and develop more responsive and data-driven broadcasting strategies.

Figure 4. Sentiment Score Trends During Broadcasting Events

Figure 4 visualizes sentiment score trends during broadcasting events over time, representing positive, neutral, and negative audience reactions. The dynamic graph illustrates fluctuations in emotional responses across different program segments, showing peaks during highly engaging or emotionally resonant moments and dips during less interactive content [35]. By capturing real-time sentiment trends, the figure emphasizes how AI-driven analytics can identify audience preferences, measure emotional impact, and support broadcasters in adapting content strategies to enhance viewer satisfaction and engagement throughout the broadcast [36].

4.2. Audience Engagement Insights

Analysis of audience engagement patterns demonstrates that interactive features, including live chats, polls, and social media integration, significantly enhance viewer participation [37]. AI analytics revealed that content optimized based on real-time sentiment feedback consistently showed higher engagement levels. The integration of AI-driven insights allows broadcasters to adapt content dynamically, improving both audience satisfaction and retention rates.

The study also highlights the relationship between sentiment polarity and engagement intensity [38]. Positive or highly emotional reactions were strongly associated with higher engagement metrics, while neutral sentiment showed weaker interaction levels. These findings underline the potential of combining sentiment analysis with audience engagement monitoring to inform content personalization and strategic broadcasting decisions.

Table 3. Audience Engagement Metrics by Content Type

Content Type	Average Comments per Session	Average Likes / Reactions	Average Shares	Average Viewing Duration (minutes)	Engagement Score*
Entertainment	120	350	45	42	0.82
News / Current Affairs	85	210	30	38	0.65
Sports	95	280	50	40	0.71
Educational / Informative	60	150	25	35	0.58
Music / Performances	110	320	40	41	0.78

Table 3 summarizes audience engagement metrics across different types of broadcasting content, including entertainment, news, sports, educational, and music programs. The metrics measured such as average comments, likes, shares, viewing duration, and overall engagement score highlight variations in audience interaction depending on content type [39, 40]. The table shows that entertainment and music content generate higher engagement levels, while educational content exhibits relatively lower interaction. These insights demonstrate how content characteristics influence audience participation and provide actionable guidance for broadcasters seeking to optimize engagement strategies across diverse program types [41].

4.3. Discussion

The results emphasize that AI-driven sentiment analytics serves as an effective and reliable tool for understanding audience behavior in interactive broadcasting platforms [42]. By leveraging NLP and machine learning models, broadcasters are able to capture complex emotional patterns embedded within large-scale audience interactions and transform them into actionable insights for content optimization. This capability enables a more precise evaluation of audience preferences, allowing media organizations to design content that is more relevant, engaging, and aligned with viewer expectations. In addition, this approach reflects the growing importance of data-driven strategies in contemporary digital media environments, where personalized and responsive broadcasting experiences have become a critical factor in maintaining audience attention and competitiveness [43].

Furthermore, the findings support the integration of sustainable media practices by promoting data-driven decision-making and reducing reliance on trial-and-error approaches in content development. The combination of sentiment analysis with audience engagement metrics provides a more comprehensive understanding of viewer behavior, enabling broadcasters to optimize resource allocation and improve operational efficiency [44]. This integrated approach not only enhances audience satisfaction and engagement levels but also contributes to the development of more adaptive and sustainable broadcasting systems. Ultimately, the use of AI-driven analytics facilitates a more strategic and responsible media ecosystem, where decisions are guided by empirical evidence and aligned with long-term sustainability objectives.

5. MANAGERIAL IMPLICATIONS

The findings of this study offer significant insights for media managers and broadcasting professionals seeking to optimize audience engagement through data-driven strategies. By leveraging AI-driven sentiment analytics, managers can gain real-time understanding of audience reactions, preferences, and emotional responses to content. This capability enables more informed decision-making in content planning, allowing broadcasters to tailor programs that resonate with viewers, maximize interaction, and enhance overall satisfaction. In particular, the ability to track positive, neutral, and negative sentiment trends provides a foundation for designing targeted interventions to increase audience participation during live broadcasts.

Furthermore, the integration of audience engagement metrics with sentiment analysis facilitates the development of personalized content strategies. Managers can identify which program types or segments generate the highest engagement and adjust scheduling, promotion, and content features accordingly. This proactive approach supports the allocation of resources more efficiently, ensuring that production efforts are focused on high-impact content and interactive features that maximize viewer engagement. By combining real-time analytics with historical audience data, broadcasting teams can continuously refine content strategies and achieve sustainable improvements in viewership and loyalty.

Finally, implementing AI-driven analytics contributes to long-term strategic planning and organizational competitiveness in the digital media landscape. Broadcasting managers can leverage insights not only to optimize individual programs but also to guide broader operational and marketing decisions, including cross-platform content distribution, social media integration, and audience community building. Additionally, the adoption of AI-enabled analytics supports alignment with sustainable media practices, such as reducing trial-and-error content production and promoting data-driven, ethical, and audience-centered broadcasting operations. These managerial applications ultimately position organizations to deliver more responsive, innovative, and culturally relevant media experiences.

6. CONCLUSION

This study demonstrates the effectiveness of AI driven sentiment analytics in understanding audience behavior on interactive digital broadcasting platforms. By integrating NLP and machine learning techniques, the research provides real time insights into audience sentiment, engagement patterns, and emotional responses across various content types. The findings reveal that positive and highly emotional content significantly enhances audience interaction, while program characteristics influence the intensity and type of engagement. These insights highlight the value of AI in enabling data-driven decision-making for content optimization, scheduling, and personalized broadcasting strategies.

The novelty of this research lies in its comprehensive framework that combines AI-based sentiment analysis with audience engagement metrics to generate actionable insights for interactive broadcasting. Unlike previous studies that focus solely on sentiment classification or engagement measurement, this study integrates both dimensions to offer a holistic understanding of viewer behavior. This integrated approach enables broadcasters to adapt content dynamically, improve real-time audience interaction, and align digital broadcasting strategies with sustainable and responsive media practices.

Future research could explore several directions to further enhance AI-driven audience analytics. First, extending the analysis to cross-platform media ecosystems including social media, OTT services, and virtual reality broadcasting would provide a more comprehensive view of audience behavior. Second, incorporating multimodal data, such as voice, video, and facial emotion recognition, can improve the accuracy and depth of sentiment detection. Finally, longitudinal studies examining the long-term impact of AI-driven content personalization on audience loyalty and retention can offer further guidance for sustainable and audience-centered broadcasting practices.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: RN, TH, and RA; Methodology: RN; Software: KA; Validation: RA and TH; Formal Analysis: RA and RN; Investigation: TH; Resources: KA; Data Curation: RA; Writing Original Draft Preparation: TH and RA; Writing Review and Editing: TH; Visualization: RN; All authors, RA, TH, RN and KA, 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 Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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