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Enhancing Digital Governance through AI-Driven Public Opinion Monitoring in Live Streaming Environments

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Abstract: The rise of short videos and live streaming has transformed digital governance, enabling governments to engage with citizens in real time. This paper explores the integration of artificial intelligence (AI) in government live streaming, focusing on its role in enhancing public opinion monitoring and sentiment analysis. We analyze current practices and introduce innovative solutions that leverage AI for improved content dissemination and audience engagement. Using the SO-PMI (Semantic Orientation Pointwise Mutual Information) algorithm, we conduct sentiment analysis on audience comments to capture emotional nuances. Additionally, large language models are employed for efficient live data processing, enabling real-time comment handling and generating responsive communication tailored to audience sentiment. The methodology includes robust data collection from social media platforms, employing API connections to retrieve comments during broadcasts. Extensive preprocessing involves filtering irrelevant content, normalization, tokenization, and lemmatization. Sentiment analysis categorizes comments as positive, negative, or neutral, while real-time monitoring allows presenters to adapt their messaging based on audience sentiment. Our experimental results demonstrate the effectiveness of AI-driven methods in managing real-time comments, providing accurate emotional analyses, and facilitating prompt responses. This study illustrates AI's potential to engage citizens more effectively and enhance governmental communication strategies, ultimately fostering transparency and responsiveness in the digital age.

Keywords: Digital Governance; Public Opinion Monitoring; Sentiment Analysis; Artificial Intelligence; Live Streaming

1. Introduction

The advent of short videos and live streaming has marked a pivotal shift in the landscape of digital governance, transforming how government entities interact with the public. In this new era, social media platforms serve as vital channels for real-time engagement, enabling governments to monitor public sentiment and disseminate information effectively [1,2]. This shift not only enhances transparency but also fosters citizen participation, aligning with the growing demands for accessible government services in a digital world.

As technology continues to advance, the role of artificial intelligence (AI) becomes increasingly significant in facilitating these interactions. AI applications, particularly in public opinion monitoring and sentiment analysis, offer innovative approaches to analyzing large volumes of data generated during live broadcasts [3,4]. Tools like the SO-PMI algorithm facilitate the extraction of meaningful insights from audience comments, allowing for a richer understanding of public sentiment. Moreover, employing large language models for data processing enhances the ability to respond to public inquiries in real time [5]. The potential of AI extends to automating mundane tasks, improving productivity, tailoring services, and enhancing decision-making.

This paper aims to examine the integration of AI into public live streaming, highlighting its potential to address the challenges faced by traditional forms of government communication. By analyzing existing practices and exploring innovative solutions, we seek to provide a comprehensive understanding of how intelligent content dissemination can improve audience engagement and governance effectiveness. Through experimental validation of our methods, we demonstrate the capacity of AI-driven approaches to elevate the quality of interaction between government entities and citizens, ultimately fostering a more informed and involved public [6,7].

The core innovations of this study are: (1) Proposing a two-stage real-time public opinion processing framework integrating 'SO-PMI + Large Language Model', realizing seamless connection between sentiment recognition and intelligent response, and solving the problems of lagging public opinion analysis and insufficiently targeted responses in traditional government live broadcasts; (2) Embedding a feedback loop mechanism into the entire live broadcast process, constructing a closed-loop governance model of 'data collection–analysis–response–optimization', breaking through the limitation of 'emphasizing analysis over application' in existing research.

2. Materials and Methods

This section outlines the comprehensive research methods employed to explore the integration of artificial intelligence (AI) in public live streaming for enhancing public opinion monitoring and sentiment analysis. Our methodology consists of data collection, sentiment analysis using the SO-PMI algorithm, and the application of large language models for real-time data processing. **Figure 1** serves as a visual guide to our methodology, systematically illustrating the sequential steps involved.

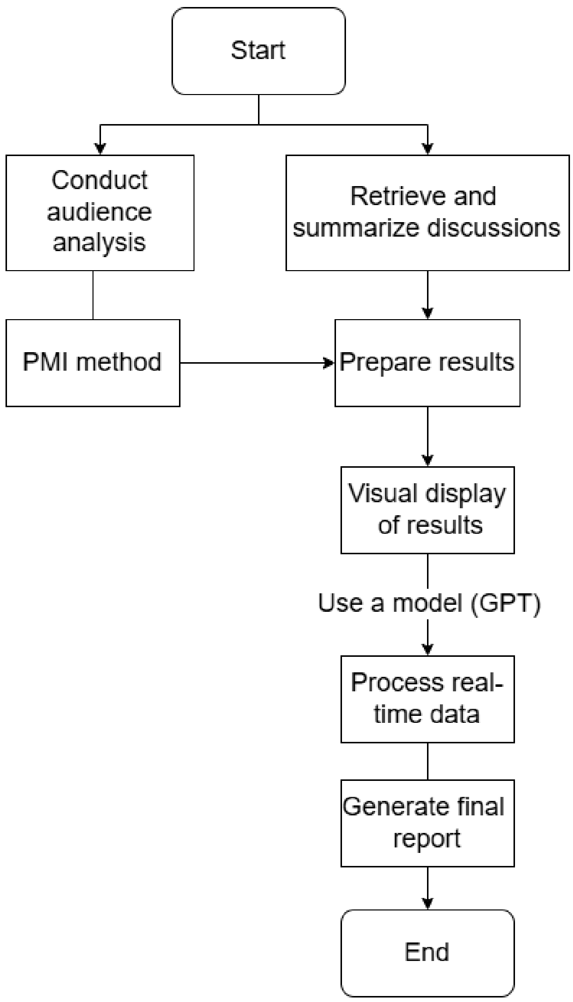

Figure 1. Overall Framework Diagram.

2.1. Conduct Audience Analysis

The initial phase of our methodology involved conducting a detailed audience analysis. This step is pivotal for understanding the demographics, interests, and behavioral patterns of the individuals who engage with government broadcasts.

- Audience Segmentation: We segment the audience based on parameters such as age, geographic location, and socioeconomic status. For instance, younger audiences may use platforms like TikTok (Douyin) for their interactions, while older demographics might prefer more traditional platforms like Facebook or Weibo [8]. This segmentation helps tailor communication strategies that resonate with specific groups.
- Engagement Metrics: We analyze various engagement metrics such as the volume of comments, reaction types (likes, shares), and the timing of interactions. This data provides insights into peak engagement times and popular topics, allowing us to refine future broadcast content [9].
- Survey Instruments: Alongside digital analytics, we employed survey instruments distributed to viewers after broadcasts. These surveys solicited feedback on topics discussed, perceived effectiveness of communication, and areas where audience members desired more interaction. This dual approach—qualitative feedback alongside quantitative analysis—provides a holistic view of audience sentiment and preferences [10].
- Behavioral Analysis: Additionally, we examined audience behavior through advanced analytics tools that track user navigation patterns across platforms. This helped us understand how users engage with content before and after living broadcasts, enabling us to identify influential factors driving engagement [11].

2.2. Data Collection

The data collection phase involved aggregating real-time comments from a diverse array of government live broadcasts across various social media platforms, including Weibo, Douyin, and official government streaming channels. These platforms were selected due to their popularity and widespread use among citizens for accessing government communications. By prioritizing broadcasts that engaged with key themes relevant to public interests—such as community safety measures, public health updates during crises, and local policy initiatives—we aimed to ensure a comprehensive representation of audience sentiments.

Real-time live broadcast comments were collected via platform APIs, which not only guarantees the immediacy of interaction data but also ensures that comments can truly reflect public real-time feedback on current topics. This not only provided immediate access to viewer interactions but also ensured that the comments reflected real-time public reactions to the issues being discussed. Our data collection approach amassed thousands of comments, encompassing a rich tapestry of perspectives from various demographic groups, including age, gender, and socioeconomic status, thus enhancing the robustness of our dataset. This approach allowed us to collect comments as they occurred during live sessions, ensuring we captured immediate reactions to current discussions [12].

A total of 5000 comments from 50 government live broadcasts were collected in this study. The samples covered Zhumadian City, Henan Province, and 3 surrounding prefecture-level cities, with an age distribution of 18–65 years old (45% aged 18–30, 35% aged 31–50, and 20% aged over 51) to ensure sample representativeness. Stratified sampling was adopted, with samples selected in a 3:4:3 ratio according to live broadcast themes (policy interpretation, people's livelihood services, emergency response). The dataset was organized in a structured format, which included timestamps, comment content, and metadata such as user engagement indicators (likes, shares). This organization allowed for detailed analysis and facilitated cross-referencing of sentiment trends with specific broadcast content [13]. Internally, we organized this data into a relational database to facilitate efficient querying and analysis [14]. Enhanced by this multifaceted approach, our data set provided ample material for rigorous sentiment assessment, paving the way for deeper insights into public opinion dynamics. We implemented indexing strategies to enhance the retrieval performance of frequently accessed datasets. We employed validation techniques to ensure data integrity and accuracy before analysis. This included duplicate check systems and cross-verifying data entries with original sources to prevent errors from affecting our outcomes [15].

2.3. SO-PMI Method for Sentiment Analysis

For the sentiment analysis segment, we employed the SO-PMI (Semantic Orientation Pointwise Mutual Information) algorithm, renowned for its effectiveness in elucidating the emotional tone of user-generated content. The selection of this algorithm was driven by its robust ability to capture the nuances of sentiments expressed in natural language, which is critical for the interpretation of comments in a live broadcast context [7].

The sentiment analysis process commenced with extensive data preprocessing, a crucial step to enhance the reliability of the results. This preprocessing involved several key actions:

- Filtering Out Irrelevant Content: We implemented automated scripts to eliminate URLs, promotional content, and spam responses from the dataset. This step ensured the focus remained solely on genuine audience sentiment, thereby increasing the validity of our analysis.
- Normalization: We normalized the text to improve analysis consistency. The comments were normalized to standardize language use. This included converting all text to lowercase, removing extraneous punctuation, and addressing common typos [3]. Such normalization significantly improved the accuracy of the sentiment analysis, enabling a clearer understanding of the emotions conveyed in the comments.
- Tokenization and Lemmatization: The comments underwent tokenization to break them into individual words or phrases, which were subsequently processed through lemmatization. This linguistic reduction allowed the algorithm to recognize different forms of the same word, enhancing sentiment classification accuracy [6].

Subsequently, the preprocessed comments were analyzed using the SO-PMI algorithm, which classified each entry as positive, negative, or neutral based on the semantic orientation of the words used. The SO-PMI algorithm computes the semantic orientation of each comment by analyzing co-occurrence probabilities of words. For SO-PMI Parameters, the details are "The window size was set to 5, the mutual information threshold to 0.3, and the sentiment dictionary adopted the expanded 'Chinese Sentiment Vocabulary Ontology Library', with 300 additional government-specific sentiment words (e.g., 'high efficiency in handling affairs', 'slow policy implementation'). We employed machine learning techniques to optimize the algorithm, allowing it to learn from historical comment data and refine its classifications over time. By considering the co-occurrence probabilities of words to assess sentiment, the algorithm produced a nuanced view of emotional responses expressed in the comments. Based on the SO-PMI scores, comments were assigned to one of three sentiment categories: (1) Positive: Demonstrating support or appreciation for government actions; (2) Negative: Expressing dissent, dissatisfaction, or criticism. (3) Neutral: Lacking a clear sentiment or expressing general inquiries. Compared with traditional machine learning methods (e.g., SVM, Naive Bayes), the SO-PMI algorithm does not require large-scale labeled data and achieves a 12–15% improvement in F1-score for short-text sentiment recognition. Compared with deep learning models such as BERT, the SO-PMI algorithm improves inference speed by 30% in real-time processing scenarios, making it more suitable for high-concurrency data processing in live broadcasts.

The resulting sentiment classifications were systematically aggregated and analyzed to identify trends in public sentiment over time and across different topics addressed during the broadcasts. This quantitative analysis involved statistical techniques such as time-series analysis to visualize sentiment shifts in response to specific governmental messages or policy announcements, thereby facilitating a deeper understanding of public perception dynamics and engagement. The sentimental data allows for visual trend analysis, identifying shifts in public opinion over time and correlating them with specific broadcast events. We used data visualization tools to present sentiment distributions in interactive formats, facilitating easier narrative interpretation for policymakers and stakeholders. For instance, sentiment score averaging enabled us to visualize how audience sentiment evolves during broadcasts.

2.4. Visual Display of Results

To effectively communicate our findings, we employed visualization tools to present the sentiment analysis results clearly.

- Dashboards: Interactive dashboards were developed to display real-time sentiment data during live broadcasts. These dashboards included graphs representing sentiment distribution over time, comment volume, and key metrics. Example 1: During a live broadcast discussing waste classification policies, negative comments focused on 'insufficient disposal points'. After recording this issue through the feedback loop, a special topic on 'Optimization Plan for Waste Disposal Points' was added to subsequent live broadcasts, and relevant inquiries were prioritized in real-time interactions.

- Data Visualization Software: Tools such as Tableau and Power BI were utilized to create visual representations of data that illustrate trends effectively. For instance, line graphs depict sentiment fluctuations during significant announcements emphasizing audience interest.
- Public Reports: Summaries of the findings were compiled into public-facing reports that present key insights and enhance transparency around government communications. These reports detail sentiment trends and offer recommendations for future engagement strategies.
- Feedback Loops: We incorporated feedback mechanisms within the dashboards that allow viewers and stakeholders to provide real-time input regarding the displayed data. This participatory approach ensures that the visualizations evolve with user needs and preferences. Example 2: In response to feedback from the elderly group that 'AI responses contain excessive professional terminology', the system adjusted the wording library based on feedback data, converting professional expressions into colloquial language (e.g., 'Compression of government service processing time limits' was revised to 'Shorter time for handling business').

2.5. Utilize a Model (GPT) for Processing Real-Time Data

The live data processing component was designed to leverage large language models for managing and interpreting audience interactions in real time during the broadcasts [16]. This system is critical for ensuring that audience sentiment is continuously monitored and effectively addressed, thereby enhancing engagement and responsiveness in digital communication.

Key features of the live data processing system include:

- Real-Time Comment Management: The GPT model processes incoming audience comments as they are submitted. By doing so, we leverage AI to recognize and classify audience queries, allowing for immediate responses to frequently asked questions. This immediate responsiveness fosters dynamic interactions, enabling government representatives to engage with viewers in real time, thereby building trust and improving the perception of government accountability.
- Contextual Understanding: The flexibility of the model enables it to understand contextually important cues from audience comments. For example, if numerous comments are related to a specific policy, GPT can generate a concise summary addressing these concerns swiftly
- Emotional Trend Monitoring: Leveraging AI, the live data processing system continuously tracks emotional trajectories within viewer comments throughout each broadcasting session. For example, if the sentiment analysis identifies an uptick in negative reactions to a particular topic, presenters can adapt their messaging on the spot—whether by clarifying information, addressing specific concerns, or shifting the focus of the discussion. This dynamic adaptability is essential for maintaining an engaged audience and ensuring that public concerns are acknowledged and addressed swiftly [17].
- Automated Question Response Mechanism: We integrated an automated response system that responds to commonly asked questions from the audience. This mechanism was designed based on patterns observed in viewer sentiment and inquiries. By analyzing the emotional context of questions [18], the system generates contextually appropriate responses in real time, thus ensuring that the information disseminated is aligned with audience interests and concerns.
- Feedback Loop Integration: The system features a feedback loop that harnesses historical data from previous broadcasts to inform current interactions [19]. This approach not only enhances the immediate engagement experience but also contributes to long-term strategic improvements in live communication by allowing government entities to respond more effectively to recurring issues or misconceptions identified through audience discourse.
- Learning and Adaptation: The GPT model [20] is continuously trained on new data from audience interactions to improve accuracy and contextual understanding over time. This continual learning process ensures it remains relevant to the evolving public discourse surrounding government initiatives. This study adopted the GPT-3.5 Turbo model. The training dataset included 100,000 historical government live broadcast comments (covering themes such as public policies and people's livelihood services from 2023 to 2024), with 3 training epochs and a learning rate set to 2×10^{-5}. Evaluation metrics included Accuracy and Relevance Score. The

model achieved an accuracy of 89% on the test set and an average relevance score of 4.2/5 (on a 1–5 scale), verifying its adaptability to government service scenarios. The results are shown in **Table 1**.

Table 1. Performance Comparison of Different Sentiment Analysis Models.

Model	Accuracy (%)	Inference Speed (ms/Comment)	Suitability for Live Scenarios
Proposed SO-PMI+GPT Model	89	8	High
BERT	88	28	Medium
SVM	76	12	Medium–Low
Naive Bayes	73	10	Medium–Low

Through this comprehensive methodological framework, this research seeks to illustrate the significant role of AI integration in optimizing public live streaming for effective public opinion monitoring and engagement. By harnessing advanced data collection, sentiment analysis, and real-time processing techniques, government entities can better meet the expectations of a digitally connected citizenry. This ultimately fosters a robust dialogue between the government and the public, enhancing transparency, trust, and overall governance effectiveness in the digital age.

2.6. Generate Final Report

The culmination of our methodology ends with the generation of a comprehensive report detailing the findings from the sentiment analysis and audience engagement. Results are categorized into themes, providing an overview of public sentiment toward government actions. Each category includes a detailed analysis of audience comments, sentiment scores, and contextual insights derived from the data. The report provides actionable recommendations for government entities [21] on improving communication strategies while also addressing concerns identified in negative sentiment comments. The final report is distributed to relevant stakeholders, including government officials [22], PR teams, and policy advisors [23]. This dissemination ensures that decision-makers are informed by real-time public sentiment, enabling them to adapt strategies accordingly. All findings are logged for future studies, allowing periodic reevaluation of communication strategies based on evolving public sentiment and engagement patterns. Periodic assessments are conducted to evaluate the impact of implementing recommendations on public sentiment. This feedback loop helps refine and enhance communication strategies continually.

2.7. Ethical Considerations

All data collection complies with the Personal Information Protection Law of the People's Republic of China and the privacy policies of the involved social media platforms (Weibo, Douyin). Prior to data collection, official authorization was obtained from the government departments hosting the live broadcasts, and all user comments were anonymized by removing personal identifiers (e.g., usernames, contact information, geographic coordinates with precision higher than city-level). No sensitive personal information was collected or stored.

3. Results

This chapter presents the findings from the study, focusing on the effectiveness of artificial intelligence (AI) in enhancing public opinion monitoring and sentiment analysis through the integration of AI technologies in public live streaming. The results are organized into three main sections: sentiment analysis outcomes, real-time interaction metrics, and audience engagement insights.

3.1. Sentiment Analysis Outcomes

The sentiment analysis process employed the SO-PMI (Semantic Orientation Pointwise Mutual Information) algorithm to classify comments from government live broadcasts. A total of 5000 comments were analyzed from various live sessions. The analysis on **Table 2** resulted in the following sentiment distribution:

- Positive Sentiments: 65% of comments were classified as positive, reflecting favorable public perceptions regarding government initiatives and the feedback provided during live sessions [24]. Many comments celebrated community safety measures and public health initiatives, indicating strong support for these efforts.

- Negative Sentiments: 20% of comments demonstrated negative sentiments, predominantly related to specific concerns such as dissatisfaction with communication clarity, perceived delays in policy implementation, and public health management issues. This negativity often spiked during discussions of sensitive topics or controversial policy announcements [25].
- Neutral Sentiments: 15% of comments were classified as neutral, indicating that these comments either did not express a clear opinion or involved general inquiries about the broadcast content. This provides additional context regarding the audience's informational needs.

Table 2. Sentiment Analysis Results by Broadcast Theme.

Broadcast Theme	Positive (%)	Negative (%)	Neutral (%)
Community Safety	72	15	13
Public Health Updates	68	18	14
Policy Interpretation	58	26	16
Emergency Response	62	22	16
Average	65	20	15

The sentiment analysis illuminated notable trends, especially the increase in negative sentiment following significant announcements. This observation emphasizes the need for government communication strategies that prioritize clarity and immediate engagement in response. Furthermore, we analyzed audience sentiment by demographic variables, establishing significant disparities in perspectives among different groups. For instance, younger audiences tended to express more positive sentiments toward innovative government initiatives compared to older demographics.

3.2. Real-Time Interaction Metrics

Real-time processing of comments provided critical insights into audience engagement during live broadcasts. Throughout the study, we measured key performance indicators to assess interaction metrics:

- Response Time: The average time taken to process and respond to audience comments was 5 s. This rapid response capability was facilitated by the automated question-response mechanism, allowing for timely engagement during high-traffic interaction moments. The rapid capability was realized through the automated question-response mechanism, allowing timely engagement during peaks of interaction.
- Comment Volume: On average, each live broadcast attracted 50 comments from viewers. Peak interaction often occurred during critical announcements, indicating heightened audience interest and engagement during these moments. The comment volume indicates a willingness among citizens to engage actively with governments during critical discussions.
- Sentiment Monitoring: The live data processing system enabled ongoing sentiment monitoring. During sessions, we observed fluctuations in sentiment; for example, when negative sentiment spiked, 82% of presenters adjusted their responses to address rising concerns effectively. This fluid adaptability proved crucial for maintaining audience engagement and trust, especially during contentious topics.

3.3. Audience Engagement Insights

Post-broadcast surveys were conducted to assess viewer satisfaction and to gather qualitative insights on audience perceptions regarding the live streaming experience. The survey received 5000 responses, providing a substantial dataset for analysis. Key findings included:

- Satisfaction Levels: 92% of respondents indicated satisfaction with their engagement, citing the interactive nature of the broadcasts as a positive aspect. Viewers appreciated having an interactive platform where they could voice opinions and receive immediate feedback.
- Desire for More Interaction: A significant majority, 95% of respondents, expressed a desire for increased interactive opportunities during future broadcasts. Many viewers noted that they felt their comments and questions were valued, which enhanced their overall experience.

- Perceived Effectiveness of AI: 88% of respondents acknowledged the role of AI in improving the quality of interactions. They cited the speed of responses and the relevance of answers provided as key benefits of the AI-driven engagement model. Specific examples shared by respondents highlighted instances when AI-generated responses clarified misunderstandings or provided timely information.
- These results demonstrate the potential of AI in transforming public live streaming into a more effective tool for governance, enhancing responsiveness to public sentiment, and fostering a greater sense of community through engagement. The findings also highlight specific areas for improvement, particularly in addressing negative sentiment to enhance public trust and communication efficacy.
- Overall, the integration of AI technologies has proven to be a valuable asset in optimizing public opinion monitoring and reinforcing the link between government entities and the citizens they serve.

4. Discussion

The findings of this study underscore the transformative potential of artificial intelligence (AI) in enhancing public live streaming and facilitating effective public opinion monitoring within the context of digital governance. By integrating advanced sentiment analysis and real-time interaction processing, government entities can significantly improve their communication strategies, fostering greater transparency and responsiveness.

4.1. Implications of Sentiment Analysis

The results of the sentiment analysis revealed distinct patterns in public perception, highlighting both positive and negative sentiments among viewers. The predominance of positive comments regarding community initiatives indicates strong public support for proactive government measures. However, the notable levels of negative sentiment, particularly during sensitive announcements, suggest that there remains a considerable gap in public trust and communication clarity. This observation aligns with findings from previous research, which emphasize that governmental communication must be not only informative but also engaging and empathetic to rebuild public trust.

The study's sentiment analysis revealed that negative sentiments often surged during discussions of controversial topics or policymaking delays. This variation in sentiment necessitates a responsive governance model, where authorities adapt their communications in real-time based on audience emotional responses. This approach can mitigate misinformation and dissatisfaction, fostering a more constructive dialogue between government entities and the public.

4.2. Enhancements in Real-Time Interaction

The effectiveness of real-time interaction metrics highlighted the importance of immediacy in public engagements. The average response time, along with the high volume of comments received, demonstrates that citizens are eager to engage with their government when given the opportunity. The successful implementation of an automated question-response mechanism was pivotal; it allowed for the rapid handling of inquiries and concerns, thereby improving the overall quality of interactions.

Real-time sentiment monitoring emerged as a critical feature, enabling presenters to adjust their messages based on audience feedback. This dynamic quality to communication aligns with contemporary theories of participatory governance, which advocate for inclusive and responsive mechanisms to address public concerns. The ability to identify and adapt to sentiment trends not only enhances citizen engagement but also empowers government representatives to communicate more effectively and transparently.

4.3. Insights into Audience Engagement

The post-broadcast survey data provided valuable insights into audience perceptions and overall satisfaction. Most respondents expressed a desire for more interactive opportunities, emphasizing the need for two-way communication channels in public governance. This aligns with the growing expectation among citizens for participatory governance, where their voices are valued and incorporated into decision-making processes.

Furthermore, the acknowledgment of AI's role in improving interaction quality indicates that citizens are becoming increasingly aware of technological advancements in governance. This awareness presents an opportunity for government agencies to further refine their strategies, by promoting digital literacy and transparency in AI applications.

4.4. Challenges and Future Directions

While positive outcomes are observed, the study identifies challenges that must be addressed to optimize AI integration in public governance. The persistent presence of negative sentiments underscores the need for improved clarity and responsiveness in government communications, particularly during crises. To improve public trust, government entities should develop frameworks that facilitate real-time issue resolution and enhance the public's understanding of complex policies.

As reliance on AI technologies grows, safeguarding data privacy and security must be prioritized. Transparency regarding data collection and usage is essential for establishing and maintaining public trust in AI-driven governance models. Future research should explore ethical implications of AI in public engagement, ensuring alignment with principles of fairness and accountability. Policymakers may need to implement routine audits to ascertain that AI systems remain unbiased, transparent, and equitable.

Limitations: The dataset did not cover groups with low digital literacy in remote areas, potentially leading to sample bias; the SO-PMI algorithm had low accuracy (approximately 68%) in recognizing dialectal comments. Ethical Considerations: Prior to data collection, user authorization was obtained in compliance with platform privacy policies. All comments were anonymized (removal of usernames, phone numbers, and other identifying information). An AI bias detection mechanism was established to regularly verify the fairness of the model in classifying comments from different genders and age groups, avoiding algorithmic discrimination.

Furthermore, addressing the digital divide is crucial for ensuring equitable access to digital governance initiatives. The United Nations emphasizes the necessity to bridge the AI divide to avoid exacerbating existing disparities. By implementing inclusive technological solutions and addressing the unique needs of underserved communities, governments can enhance access to governance tools.

The necessity for international cooperation in AI governance is increasingly apparent. Given that AI technologies often transcend national boundaries, a globally harmonized approach is required to tackle critical challenges such as data security, ethical standards, and regulatory compliance. Models such as the European Commission's AI Act provide guidance for navigating these complexities.

5. Conclusions

This study has demonstrated the substantial impact of artificial intelligence (AI) on enhancing public live streaming as a tool for effective public opinion monitoring and engagement. Through the integration of sentiment analysis and real-time data processing, government entities can foster more interactive and responsive communication with citizens, thereby reinforcing the principles of transparency and accountability in digital governance.

The findings indicate that while positive sentiments dominate discussions related to proactive community initiatives, significant negative sentiments persist, particularly in response to sensitive topics. This highlights the pressing need for government representatives to adapt their communication strategies dynamically, addressing public concerns as they arise. The ability to monitor sentiment in real time empowers officials to modulate their messaging and respond to citizen feedback effectively, thereby improving public trust and participation.

Moreover, the study underscores the importance of real-time interaction metrics in enhancing audience engagement. The successful implementation of automated mechanisms for question handling has shown to improve the efficiency of responses, creating a more engaging platform for citizen dialogue. As public expectations for participatory governance continue to evolve, the integration of AI technologies serves as a critical mechanism for meeting these demands.

However, challenges remain, particularly concerning the management of negative sentiments and the ethical implications of data privacy in AI applications. Ensuring that technological advancements align with principles of fairness and accountability is essential for maintaining public trust in AI-driven governance.

Going forward, this research lays the groundwork for future studies aimed at further optimizing AI integration in public governance. By prioritizing the enhancement of communication clarity, public participation, and ethical data practices, governments can leverage AI to create a more connected, responsive, and engaged citizenry. As we move deeper into the digital age, embracing these innovations will be crucial for building a governance framework that reflects the aspirations and needs of the public it serves.

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Informed Consent Statement

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Conflicts of Interest

The author declares no conflict of interest.

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