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# Design and Implementation of a Public Opinion Network Analysis System Based on Derived GANs

-- A Case Study of Trump Tariff-Related Public Opinion

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**Abstract:** This thesis addresses the complex public opinion monitoring challenges arising from the Trump administration's tariff policies by proposing an innovative public opinion analysis framework based on Generative Adversarial Networks (GANs). The framework integrates multiple specialized GAN models (e.g., T-GAN, Senti-GAN, CM-GAN) to tackle issues such as data scarcity, sensitive information deletion, and insufficient multimodal fusion in traditional public opinion monitoring. By combining GAN-generated data with the RoBERTa-BiLSTM-Multihead Attention (RBMA) large language model, the system is expected to significantly outperform traditional unsupervised methods and purely generative models in tasks such as term recognition, stance classification, and risk warning. This architecture not only reduces the dependency on and cost of annotated data but also exhibits high robustness, providing an efficient and reliable solution for public opinion monitoring amid political and economic conflicts such as tariff wars.

**Keywords:** Component; Public Opinion Analysis; GAN; Large Language Models.

## 1. Introduction

In recent years, the international landscape has undergone sudden changes, with trade conflicts between nations becoming increasingly pronounced. In 2018, after Donald Trump assumed the presidency of the United States, trade tensions among countries escalated rapidly. On the tariff issue, the U.S. imposed 25% tariffs on $50 billion worth of Chinese goods, prompting retaliatory measures from China. Two years later, after a series of negotiations, China and the U.S. signed the Phase One trade agreement, which eased tensions but left core issues unresolved. In 2025, Trump returned to the White House and immediately relaunched and escalated tariff measures under the banner of "America First 2.0." On April 2, Trump signed the Reciprocal Tariff Act, announcing the imposition of "reciprocal tariffs" on all trading partners, with the rate for China set at 34%, later even raised to 145% amid trade confrontations, as shown in Figure 1.

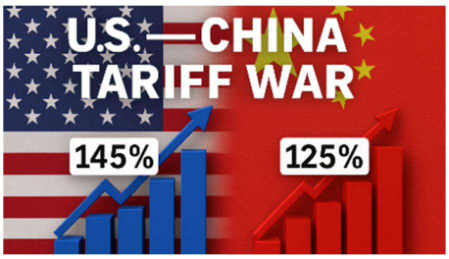


**Fig 1.** Illustration of the US-China tariff conflict.

This policy instantly caused an uproar. In addition, the U.S. adopted measures such as increasing tariff rates on imports from countries surrounding China and repatriating Chinese students to further pressure China. However, having been well-prepared after the previous trade war, China not only held leverage as the largest producer of rare earths, forcing the U.S. to compromise, but also supported semiconductor technology companies to break monopolies, minimizing losses in this tariff war.

The prolonged trade rivalry between these major powers naturally sparked numerous public opinion incidents. On China's leading social platform, Weibo, nearly 1,000 trending topics related to the "tariff war" emerged, with an explosive increase after April 2 and another peak in May when China and the U.S. signed a joint statement. Simultaneously, the tariff issue garnered widespread discussion internationally, with the global community considered that the U.S. approach hads seriously violated WTO rules undermined the rules-based multilateral trading system. The tariff issue concerns the public, businesses, and government departments worldwide. The proposal of "reciprocal tariffs" instantly ignited public opinion, with internet platforms flooded with diverse information—comments from netizens on government policy posts, perspectives from international affairs commentators, and reports from media outlets. Public opinion information spread online in the form of text and images. To monitor public opinion on the tariff war, a model capable of processing long texts and certain multimodal data is essential to handle complex information from various channels. Additionally, given the vast amount of information involving sensitive topics such as government positions and official statements by leaders, the model should also be able to recover and reconstruct data that may have been deleted due to sensitivity.

Traditional public opinion monitoring methods include manual inspections and media monitoring, clustering, and NLP language models. However, manual monitoring lacks efficiency and suffers from delayed responses. Unsupervised methods like clustering and LDA have poor analytical capabilities for generated data and lack the ability to address specific public opinion tasks. Although NLP language models can capture context, most large models lack semantic labels in their training data, making them inadequate for analyzing sudden public opinion incidents in today's information dissemination networks.

To address this, this paper proposes for the first time a public opinion network analysis system based on Generative Adversarial Networks (GAN). This system can integrate long texts and other modal information such as images, efficiently generating an adversarial framework with minimal information. The generator complements potentially misdeleted sensitive samples in the information, while the discriminator simultaneously verifies the authenticity of the information and assesses sentiment, providing a real-time, robust, and low-cost new paradigm for parsing the complex public opinion landscape triggered by Trump's tariff policies.

# 2. Related Works

Generative Adversarial Networks (GANs) were proposed by Goodfellow et al. in 2014 [1]. They primarily consist of two neural network models: the generator and the discriminator. Through adversarial training of these two networks, the generator is driven to produce data that resembles the distribution of real data, while the discriminator attempts to distinguish between generated data and real data, thereby training the model in a low-cost manner. Early successes of GANs were primarily in the field of image generation. In 2015, Radford et al. proposed DCGAN (Deep Convolutional GAN), whose major innovation was the successful introduction of Convolutional Neural Networks (CNN) into the architecture of both the generator and discriminator in GANs [2]. This enabled both the generator and discriminator to learn local and global features of images in an end-to-end manner, significantly improving the quality and resolution of generated images and providing a stable and reliable CNN-based foundation for subsequent research. However, the discrete nature of textual data made it impossible for gradients to be directly propagated from the discriminator to the generator, which became an obstacle for applying GANs to text generation. In 2017, Yu et al. proposed SeqGAN, which innovatively transformed the sequence generation process into a reinforcement learning problem, where the discriminator acts as a reward function, providing gradient update signals to the generator through policy gradient methods [3]. This approach cleverly circumvented the gradient issue caused by the discreteness of text, enabling GANs to effectively generate grammatically coherent text sequences and solving the challenge of discrete sequence generation. Subsequently, the rise of the Transformer architecture brought new possibilities for long-text generation. In 2021, Hudson et al. proposed Transformer-GAN (T-GAN), whose core innovation was replacing CNN entirely with the self-attention mechanism of Transformer as the core of both the generator and discriminator[4]. This allowed the model to efficiently generate long texts while maintaining global semantic consistency, greatly meeting the need for data augmentation of long texts (such as news reports) in public opinion analysis.

The evolution of public opinion monitoring technology has generally progressed from traditional machine learning to deep learning. Early methods heavily relied on unsupervised learning. In 2003, Blei et al. proposed LDA (Latent Dirichlet Allocation), whose innovation lies in representing documents as probability distributions of latent topics and mapping words to topics, thereby automatically discovering abstract topics from text corpora without prior labeling[5]. This method laid the foundation for unsupervised methods in public opinion analysis tasks and was often used in combination with clustering algorithms such as K-means. However, these methods struggled to capture nuanced semantics and complex sentiment tendencies, gradually falling short of modern society's demands for complex public opinion analysis. The rise of deep learning brought a turning point. In 2018, Google's AI team proposed BERT (Bidirectional Encoder Representations from Transformers). Its revolutionary innovation was the adoption of the Transformer encoder and the "Next Sentence Prediction (NSP)" pre-training task, addressing the limitation of traditional language models that could not simultaneously utilize contextual information. This achieved breakthrough progress in tasks such as sentiment analysis and stance classification, elevating the accuracy of public opinion monitoring and the depth of semantic understanding to new heights[6]. Subsequently, in 2019, Liu et al. optimized BERT and proposed RoBERTa (A Robustly Optimized BERT Pretraining Approach) [7]. Its innovations included empirically removing the NSP task, adopting larger batch sizes and longer training times, using dynamic masking, and training on more extensive data. These improvements addressed the issue of insufficient training in BERT, contributing a more powerful and stable pre-trained model that better accomplished public opinion analysis tasks. The relevant work has demonstrated great potential in public opinion analysis, laying a foundation for the subsequent public opinion analysis to enter an efficient and precise stage

# 3. Method

In response to the complex public opinion landscape triggered by the tariff war initiated by the Trump administration, this paper proposes a comprehensive public opinion analysis system. It primarily consists of two main components: firstly, leveraging GAN models for data generation to address the complexity of public opinion, and secondly, utilizing large-scale models for public opinion monitoring to conduct further analysis of the data.

## 3.1. Generative Adversarial Networks (GANs)

The basic Generative Adversarial Network (GAN) model primarily consists of two neural networks (CNN): the generator and the discriminator. The input to the generator is random noise, and its output is generated samples. Its objective is to make the generated samples as close as possible to real samples in order to deceive the discriminator. The input to the discriminator is either real samples or samples generated by the generator, and its output is a probability value indicating the likelihood that the input sample is real. Its goal is to accurately distinguish between real and generated samples. The generator and discriminator of the GAN model are trained alternately. During the iterative process, the discriminator is trained first to enhance its ability to differentiate between real and fake data, followed by training the generator to improve its generative capability. Ideally, as training progresses, the data distribution of the generator will gradually approach the distribution of real data, and the discriminator will become unable to accurately distinguish between the two. The schematic diagram of the GAN model is shown in Figure 2.

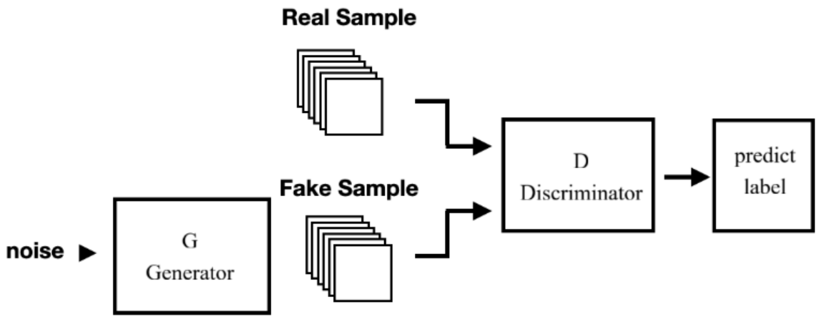


**Fig 2.** Schematic diagram of the GAN model

With further research, GAN models have been optimized, giving rise to various GAN models with broader application domains, higher accuracy, and stronger robustness. For public opinion analysis and monitoring in the context of the tariff war, the proposed GAN model must possess the following characteristics and functionalities: **Data Completion**: The vast amount of online public opinion information is complex, and sub-topics related to tariff issues often suffer from corpus deficiencies and uneven spatiotemporal distribution. Using GAN models, the corpus can be expanded without altering semantic information (e.g., content, sentiment), thereby addressing the issue of insufficient data for models. **Prediction and Simulation**: Through conditional control, generative adversarial networks can map policies that have not yet been enacted into corresponding contextualized public opinion texts. This enables prospective analysis of potential public opinion trend for subsequent sentiment and topic models without relying on real data samples. **Desensitization**: To address the sensitivity of political discourse, GAN models should be capable of removing sensitive content and regenerating similar content for model training.

As a data generation method for a novel public opinion monitoring solution, GAN models should possess the aforementioned functionalities to tackle the challenges posed by massive and difficult-to-process public opinion data. Below, several GAN models that meet these requirements and exhibit strong performance are introduced.

SeqGAN (Sequence GAN) is a type of generative adversarial network specifically designed for discrete sequence data (such as text). Its core idea is to model the sequence generation problem as a reinforcement learning process, utilizing the reward signals provided by the discriminator to train a generator based on recurrent neural networks (e.g., LSTM) through policy gradient methods[8]. As a result, SeqGAN can effectively generate text sequences that adhere to grammatical rules and maintain semantic coherence. For public opinion monitoring, the core value of SeqGAN lies in its ability to generate high-quality, diverse simulated text data, providing critical support for the training, testing, and data augmentation of public opinion analysis models.

T-GAN (Transformer GAN) is a type of generative adversarial network where the convolutional networks are replaced entirely by Transformer structures. The core idea is to substitute both the generator and discriminator of the GAN with Transformers composed solely of attention mechanisms and feedforward networks. Leveraging the advantages of Transformers, it enables parallel computation and global dependency modeling. Parallel computation eliminates the need for recursion, allowing it to output long sequences of continuous data in a single pass on GPUs, meeting the real-time supplementation requirements of public opinion monitoring. Thus, T-GAN can generate long texts promptly in response to sudden public opinion incidents while ensuring global contextual semantic consistency, aligning with the data generation demands of public opinion monitoring.

CM-GAN (Cross-modal GAN), employs two autoencoders and two sets of discriminators to place text and image data into the same semantic space, enhancing inter-modal consistency and enabling multimodal data generation[9]. Because Cross-modal GAN designs a latent space within the generator for three modalities—text, numerical, and image—it can synthesize complete samples for public opinion monitoring in a single pass, including time-related heat indicators, corresponding thematic texts, and event illustrations. In contrast, traditional GANs can only output single-modality data.

SentiGAN (Sentiment GAN) is a type of generative adversarial network model capable of generating texts with multiple emotion categories[10]. It proposes an unsupervised framework for generating diverse emotional texts. Its core idea involves the collaborative training of multiple generators and a multi-category discriminator to produce high-quality, diverse texts with different emotional labels. Multiple generators are responsible for generating texts of different emotions, while the multi-category discriminator simultaneously distinguishes the authenticity of the texts and their associated emotions. This principle enables it to unsupervisedly produce high-fidelity public opinion samples with clear emotional labels, meeting the demand for multi-emotion polarity data in public opinion monitoring.

**Table 1.** Comparison of GAN Models

| *GAN* | *Core Advantage* | *Application scenarios* |
|---|---|---|
| SeqGAN | generating short texts with coherent grammar | The enhancement of public opinion comment data |
| TGAN | Parallel computing, generating long text | Analysis of policy news public opinion |
| SentiGAN | generating multi-emotion text | Emotional analysis and prediction of public opinion |
| CMGAN | Aligning graphics and text across modalities | False identification of graphic and textual public opinions |

The core advantages of the aforementioned GAN model and their applications in public opinion scenarios are summarized in Table 1. The evolution of the aforementioned GAN technologies has provided new tools for public opinion analysis. Traditional public opinion monitoring techniques (such as LDA and BERT), while capable of processing conventional text, exhibit limitations in addressing issues like data scarcity and multimodal fusion. In contrast, the generative capability of GANs can precisely compensate for these shortcomings. The integration of both approaches demonstrates significant potential in the context of public opinion monitoring.

### 3.2. Public Opinion Analysis Large Language Models

Large language models have become the mainstay of contemporary public opinion monitoring. Leveraging their powerful language understanding and generation capabilities, they can capture, aggregate, and perform in-depth analysis of massive amounts of public opinion information from diverse sources. They are capable of accurately identifying topic evolution and sentiment trends. Their functionality plays a critical role in public opinion monitoring by generating opinion summaries, conducting data analysis, and mapping dissemination pathways. They also provide comprehensive and efficient decision-making support for governments and media organizations. Below are several mainstream large language models:

GPT-4, developed by OpenAI, is a large multimodal language model based on the Transformer Decoder. It can process massive amounts of multilingual and cross-platform posts in a single input and directly generate summaries of event timelines, stance distributions, and sentiment trends. It excels in tasks such as public opinion summarization and crisis simulation. Through its chain-of-thought reasoning capability, GPT-4 achieves logically accurate causal inference, significantly contributing to predicting secondary impacts of public opinion. Additionally, its native multilingual capability almost eliminates the need for translation, enabling real-time analysis of public opinion in various low-resource languages. For tariff-related issues, this advantage allows GPT-4 to process more information from around the world, providing comprehensive coverage of the global impact of tariff events.

BERT is a pre-trained deep bidirectional language model based on the Transformer Encoder. Its bidirectional Transformer architecture enables it to capture subtle emotional differences in local contexts, allowing it to accurately identify various emotions in the corpus and deepen semantic understanding. When dealing with the massive volume of public opinion information related to tariff events, it can achieve effects such as filtering spam, aggregating subtopics, identifying sentiments, and issuing early warnings for hotspots. Subsequent improvements to BERT led to the development of RoBERTa, a large language model more suitable for public opinion monitoring. Building on BERT, RoBERTa removes the Next Sentence Prediction (NSP) task, adopts dynamic masking, and expands the training data, resulting in more accurate semantic representations. In public opinion monitoring, it can more accurately capture emotional tendencies, hotspot entities, and sudden events in public opinion information, providing more reliable signals for real-time early warnings, topic classification, and risk traceability. Subsequently, researchers combined RoBERTa, Bidirectional Long Short-Term Memory (BiLSTM), and multi-head attention mechanisms to propose a language model (RBMA) that better understands contextual structures and textual dependencies, thereby accurately identifying the emotional tendencies of texts [11]. This aligns perfectly with the tariff events triggered by the Trump administration. The sudden tariff policies and unexpected events require large language models capable of effectively processing long-text information and capturing public sentiment fluctuations for analysis and prediction.

## 4. Experiment

The GAN-based large language model for public opinion monitoring proposed in this paper is evaluated through experiments divided into two main parts. The first part focuses on data generation, which involves using GAN models for data synthesis prior to large language model pre-training, followed by a data cleaning process. The second part details the pre-training methodology for the large language model and presents a comparative analysis between the large language model and traditional unsupervised methods for public opinion monitoring tasks.

### 4.1. Data Generation

In the data generation framework, this study constructs multiple types of datasets tailored to the characteristics of Trump tariff-related public opinion for training GAN models [12]. The datasets include: news corpora (e.g., RealNews, media reports from Factiva database), social media texts (e.g., news comment datasets from Kaggle, Reddit, and Twitter comment datasets, etc.), and policy documents (e.g., UK Government Policy Papers, official White House websites, etc.). In selecting data sources, emphasis should be placed on choosing appropriate, high-quality labeled public opinion datasets to ensure unified standards for sentiment or topic annotations, preventing GAN models from learning noisy distributions. Additionally, to avoid mode collapse (a common issue in GAN training where the generator outputs only a limited number of repetitive samples, losing diversity), it is essential to ensure that the training sample size is ≥10,000[13]. Finally, the selected dataset scenarios should align with tariff-related public opinion, with datasets containing keywords such as "news," "tariffs," and "politics" being most suitable.

For the task of generating tariff-related public opinion texts, this study recommends the following generative adversarial network models, which are functionally complementary and can also operate independently: TGAN focuses on reasoning and generating long policy texts, SentiGAN controls the emotional stance expression in short texts, and CMGAN achieves cross-modal semantic alignment between text and images. These three models address the needs of in-depth public opinion analysis, emotion and stance reinforcement, and multimodal dissemination, respectively.

Data cleaning is particularly crucial both before and after using GAN models for data generation [14]. First, source data must be denoised. If false information in the original data is not cleaned, it will be amplified by the GAN models. This involves filtering out advertisements, tweets from bot accounts, non-English topical tweets, and repetitive news reports. Second, deep cleaning is necessary to ensure the source data is accurate, valid, and of high quality. After generating data using the aforementioned GAN models, secondary cleaning is required to ensure the accuracy of the generated data. Logical contradictions in the generated data could mislead subsequent decisions of large language models. Different cleaning strategies are applied to different GAN models: for TGAN, factual errors in long texts must be addressed; for SentiGAN, semantic and emotional inconsistencies need attention; for CMGAN, text-image semantic conflicts should be resolved. Post-generation cleaning ensures the validation of public opinion facts, guaranteeing logical consistency and sample reliability.

## 4.2. Comparative Experiment

In the framework combining GAN and large language models proposed in this study, it is important to couple GAN-generated data with large language model training. This paper recommends adopting the RoBERTa-BiLSTM-Multihead Attention architecture (RBMA). To validate the effectiveness of integrating this architecture with GAN models, three types of methods should be selected for comparative experiments: unsupervised methods as the traditional control group (primarily K-means clustering), supervised methods as the conventional large language model control group (RBMA without GAN integration), and zero-shot purely generative methods (GPT-3.5) as the different large language model control group. By comparing these methods with the core theme of this study, the superiority of the proposed architecture can be verified.

The unsupervised method combines K-means clustering and LDA (Latent Dirichlet Allocation), relying solely on textual statistical features. LDA performs topic modeling and feature extraction, and its output serves as the input for K-means clustering[15]. This combined unsupervised method accurately and effectively clusters public opinion data into different groups, inferring public opinion values such as heat trends by statistically analyzing the topics of concern within each cluster. However, the results generated by unsupervised methods may be difficult to interpret and evaluate, and the choice of algorithms and parameters significantly impacts the outcomes, which may not necessarily align with the requirements of tariff-related public opinion tasks. The zero-shot purely generative method (GPT-3.5) is also an unsupervised approach, pre-training on open-domain corpora with unsupervised objectives and directly generating results from natural language instructions during runtime without the need for annotations. The supervised method, the RBMA model, leverages general pre-trained knowledge and fine-tunes model parameters using labeled tariff-related samples to achieve standard public opinion monitoring functionality. The fundamental difference between unsupervised and supervised methods lies in whether the training data contains labels, which determines whether a predefined label system is required for public opinion monitoring and whether the method can analyze sudden public opinion incidents.

Below is the comparative experimental procedure between the public opinion monitoring model, which couples GAN models with the fine-tuned RBMA large language model, and the three aforementioned models:

First, the testing environment is unified. The same set of 1,000 real tariff-related public opinion data instances (including text and images) is selected as the raw input for all models. The parameter scale of each model is kept consistent (all models except GPT-3.5 are controlled at 110 million parameters). Additionally, the RBMA architecture is ensured to be identical for the two supervised methods.

The same testing tasks, such as stance classification and risk warning, are assigned to all four methods. To evaluate performance, the following metrics are provided: Accuracy, Precision, Recall, and F1-score, which are used to precisely measure the task performance of the methods [16]. Accuracy indicates the proportion of correctly predicted samples among all predictions. Precision represents the proportion of truly correct samples among those predicted as correct. Recall measures the proportion of correctly predicted samples among all actual correct samples. F1-score is defined as the harmonic mean of Precision and Recall, reflecting the balance between these two evaluation metrics. It is calculated using the formula:

$$2 \times \frac{Precision \ \times Recall}{Precision + Recall} \tag{1}$$

For public opinion monitoring objectives, in order to minimize the risks of missed detections and false positives, it is essential to maximize both Recall and Precision, thereby improving the F1-score. In the context of politically sensitive tariff-related public opinion analysis, a higher F1-score indicates greater practicality of the framework in corresponding scenarios, effectively avoiding ethical risks associated with over-censorship while ensuring the model's capability to capture social risks.

The performance results after testing are presented in the Table 2:

**Table 2.** Reference table for comparative experiments

| *Model* | *Accuracy* | *stance classification* | *risk warning* | *Parameter scale* |
|---|---|---|---|---|
| Kmeans+LDA | | | | |
| RBMA | | | | |
| GPT 3.5 | | | | |
| GAN+RBMA | | | | |

Through performance testing, it can be predicted that the GAN-enhanced RBMA model will demonstrate comprehensively superior performance over traditional BERT models and other unsupervised methods in tariff-related public opinion tasks such as term recognition, stance classification, and risk warning. Additionally, supplementary tests such as response speed testing and robustness testing can be conducted, which would reveal that the parameter design of the proposed architecture also reduces response latency while maintaining a lower performance decay rate. This is because traditional supervised models rely on annotated data and cannot cover complete political public opinion scenarios, whereas the architecture coupled with different GANs leverages GAN's capability to generate large volumes of data from limited samples. This effectively addresses issues such as scarcity of stance annotations and lack of simulation data, while simultaneously reducing the cost of obtaining real annotated data and improving model pre-training efficiency.

# 5. Conclusion

This thesis addresses the public opinion monitoring challenges triggered by the Trump administration's tariff war and proposes an innovative model framework based on Generative Adversarial Networks (GANs). By integrating multiple specialized GANs (such as T-GAN for generating long texts, SentiGAN for controlling sentiment polarity, and CM-GAN for achieving cross-modal alignment), the framework effectively resolves pain points in traditional public opinion monitoring, including data scarcity, sensitive information deletion, and insufficient multimodal fusion. Through subsequently predictable multi-method comparative experiments, the architecture coupling GAN-generated data with the RBMA large language model significantly outperforms traditional methods in tariff-related public opinion tasks, demonstrating notable improvements in term recognition accuracy, stance classification, and F1-scores for risk warning compared to conventional RoBERTa methods. Furthermore, the proposed architecture not only reduces the cost of collecting annotated data through data completion and reconstruction but also provides real-time analytical support for public opinion speculation of sudden tariff policies with high robustness, offering a novel and efficient approach for public opinion monitoring tasks amid complex political and economic conflicts. Simultaneously, the system also has several limitations and shortcomings, such as a lack of real-time response to sudden public opinion incidents, necessitating the addition of a real-time analysis module from policy release to public opinion prediction in subsequent research to avoid latency. Further optimizations regarding the integration of GANs and large language models for public opinion analysis hold significant potential and await exploration by researchers.

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