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Public Opinion Evolution Driven by Large Language Models

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Abstract. The rapid proliferation of social media has fundamentally reshaped the formation and dissemination of public opinion, posing significant challenges to social governance and public decision-making due to its high complexity, abrupt emergence, and amplification effects. Conventional public opinion diffusion studies, including diffusion dynamics and network-based models, are effective in capturing macroscopic propagation patterns, yet they exhibit inherent limitations in semantic understanding, emotion perception, and cross-cultural generalization. Recent advances in Large Language Models (LLMs) have introduced new opportunities for public opinion research by enabling fine-grained semantic analysis and robust emotion recognition in multilingual environments. Existing studies demonstrate that LLMs are effective in opinion and emotion detection, misinformation identification, and complex sentiment analysis, while also revealing limitations such as language bias and insufficient representation of extreme or minority viewpoints. Moreover, LLM-based approaches have been explored for public opinion simulation and deviation analysis, showing the ability to approximate collective behaviors and opinion evolution under realistic communication settings. In addition, LLMs have been applied to public opinion event detection and information activity analysis, including narrative frame classification and real-time policy communication assessment. To further enhance modeling fidelity, emerging hybrid frameworks, such as LLM-integrated diffusion models, combine the reasoning capabilities of LLMs with traditional dynamic propagation mechanisms, yielding improved predictive performance and interpretability. This survey systematically reviews recent progress in LLM-driven public opinion analysis, simulation, and event detection, discusses key challenges and open issues, and outlines future research directions for advancing public opinion governance and decision-support systems.

Keywords: Large Language Models, Public Opinion Analysis, Social Media Diffusion, Opinion Dynamics

1. Introduction

In the contemporary information environment, network public opinion has become an important force affecting social cognition and policy decision-making. Its propagation process is often accompanied by multi-agent interaction and emotional resonance, showing complexity, suddenness and amplification effects, which is easy to trigger widespread attention and social reactions in a short period of time, thus bringing far-reaching challenges to social governance and public decision-

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making. Traditional research on public opinion mostly relies on the propagation dynamics model and network diffusion model. These methods can describe the macro mechanism of the diffusion of public opinion, but it is difficult to effectively capture the semantic connotation, emotional fluctuations, and the characteristics of public opinion in cross-lingual and cross-cultural contexts.

With the rise of large language models represented by ChatGPT and DeepSeek, researchers have gradually introduced them into the field of public opinion analysis. Large Language Model (LLM) has powerful semantic modeling, sentiment analysis and multi-language processing capabilities, and can complete complex emotion recognition, public opinion simulation and false information detection under the condition of few or even zero samples, to make up for the shortcomings of traditional methods. Specifically, the application of LLM in the study of public opinion evolution is mainly reflected in the following aspects. In the aspect of sentiment and opinion detection, LLM can effectively identify the sentiment tendency in multi-language and multi-domain texts, and improve the accuracy and adaptability of political public opinion analysis through few-shot and zero-shot learning. In the simulation of public opinion and bias analysis, LLM can be used to simulate public opinion and predict election behavior, but it also exposes cultural, linguistic and ideological biases caused by the uneven distribution of corpus. In public opinion event detection and information activity analysis, LLM shows significant advantages in identifying false information, parsing narrative framework and supporting policy research. Fusion modeling methods have become an important trend of current research, such as combining LLM with propagation dynamics model or agent-based modeling to build a more realistic and multi-level simulation system of public opinion evolution. This kind of hybrid model not only improves the accuracy of public opinion prediction, but also enhances the model's ability to capture complex social interaction and semantic information [1].

At present, LLM still faces many challenges in public opinion research, including implicit bias in model output, insufficient cross-language and cross-cultural adaptability, limited real-time response ability, and weak interpretability. This paper aims to systematically review the application progress of LLM in public opinion analysis and evolution research, compare its advantages and disadvantages with traditional models, and prospect the development direction of fusion modeling, human-computer collaboration and cross-cultural adaptability.

2. Traditional approaches to opinion dynamics

In the early stage of public opinion research, due to the similarity in characteristics between the spread of public opinion and the spread of infectious diseases, both of them rely on the diffusion of network structure, and there are typical processes of "super spuser" and "susceptitive-infection-removal". Opinions in public opinion are "contagious" like viruses, and users will go through similar stages of receiving, spreading and eventually leaving. Emotional resonance can be likened to symptom manifestation, while refutation or cognitive immunity is equivalent to the formation of herd immunity. Therefore, traditional epidemic models are often borrowed from public opinion evolution modeling. Many scholars have introduced the infectious disease model to initially model the spread of network public opinion. The academic community mainly relies on the propagation dynamics and network diffusion model to describe the propagation law of information in social networks. The model based on the dynamics of infectious diseases is widely used to simulate the process of public opinion spreading, and the diffusion of information is likened to the spread of infectious diseases, where the "susceptible" corresponds to the individuals who have not contacted the public opinion, the "infected" represents the group participating in the transmission, and the "recovered" represents the users who have lost interest in the public opinion or stopped the

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diffusion. This kind of model can reflect the life cycle of public opinion more intuitively, construct the relationship between "susceptible", "infected" and "recovered", assume that the population is homogeneous, and form a simple network structure, such as the dynamic evolution process from initial spread to peak and then to recession.

At the same time, the network diffusion model is also an important tool to study the evolution of public opinion. Among them, Independent Cascade Model (ICM) [2] and Linear Threshold Model (LTM) are two representative propagation models based on social network structure [3]. The independent cascade model emphasizes that information propagates among neighbor nodes in a probabilistic manner. The core mechanism of the independent cascade model is that each activated node, that is, an individual who receives the information and is willing to disseminate it, independently influences its non-activated neighbors with a certain probability in a single attempt. This model highlights the randomness of information dissemination and the role of contact opportunities, and is suitable for simulating public opinion events with strong contingency and viral diffusion characteristics such as rumors and hot news.

Different from them, the linear threshold model focuses on describing the joint effect of social influence and group pressure on individual decision-making [4]. In this model, each individual possesses an activation threshold, which is usually related to its personality, conformity degree, or critical ability. At the same time, the influence weight of each neighbor on it may be different. When the sum of the influence weights of the activated neighbors exceeds the threshold of the individual, the individual will be activated and adopt the information or opinion. The linear threshold model emphasizes the importance of group dynamics and cumulative social influence in the formation of public opinion, and is more suitable to simulate the propagation phenomena that rely on group interaction and pressure transmission, such as consensus formation of public opinion and diffusion of social movements. These models provide an important theoretical basis for understanding the basic laws of public opinion diffusion.

However, these methods have certain limitations when dealing with complex public opinion environment. On the one hand, they mainly focus on the quantity and structural characteristics of information dissemination, lack of in-depth description of semantic content and emotional elements, and it is difficult to reveal the potential attitude change and emotional resonance in the evolution process of public opinion. On the other hand, traditional models have insufficient performance in cross-lingual and cross-cultural multiple public opinion scenarios, and are difficult to effectively adapt to the massive, diverse and complex context public opinion data in the current social media environment. These shortcomings provide an opportunity for the subsequent introduction of LLM, so that it can supplement the shortcomings of traditional modeling methods in semantic understanding and emotion recognition.

3. LLM applications in opinion dynamics

3.1. Sentiment and opinion detection

In public opinion analysis, sentiment and opinion detection is the core link. Emotions and opinions are subjective judgments of human beings. The evaluation standards given by each person are very different, and the understanding of other people's views will also be different, so the difficulty of public opinion analysis will be greatly improved. With the continuous development of large language models, they show significant advantages in multi-language and multi-domain sentiment analysis and other fields. Studies show that LLM can capture more delicate emotional features in complex cross-lingual environments, adapt to differences in opinions in different contexts, and

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further alleviate problems such as opinion misunderstanding caused by language barriers. For example, in the field of e-commerce, LLM can quickly and effectively browse and input the public opinion information it reads, further identify and judge false comments, so as to help enterprises optimize decisions and reduce certain losses. In the research of social public opinion, based on its complex emotional modeling ability, it is helpful for scholars and the industry to grasp the public position more accurately and make plans more suitable for solving the current public opinion and social discussion problems [5].

LLM also has diversity in learning paradigms. This paper focuses on few-shot learning and zero-shot learning and compares them. Few-shot learning performs better than zero-shot learning in political public opinion analysis tasks, especially in the low-resource minority language environment, it can achieve better generalization performance with limited labeled data [6]. This shows that the reasonable use of a small number of examples can significantly improve the adaptability and robustness of the model for the task of public opinion segmentation. Similarly, Few-shot has higher stability and accuracy in multi-dimensional emotion extraction and cross-task sentiment analysis [7]. At the same time, although Zero-shot has the convenience of "ready-to-use", it is more prone to deviation in complex contexts, such as sarcasm, metaphor and other expressions that require deep understanding. This difference also reminds us that in highly sensitive tasks such as political public opinion and cross-cultural communication, reasonably introducing few-shot examples is often more reliable than completely relying on zero-shot examples.

Fake review identification and structured modeling of complex emotions further highlight the application potential of LLM. By combining Chain-of-thought prompting, LLM can not only output sentiment classification results, but also show the reasoning process synchronously, thereby improving the transparency and interpretability of analysis [8]. This feature is of great value in the research of political public opinion and social governance, which helps to enhance users 'trust in the results of the model, and promotes the evolution of sentiment analysis to higher-order opinion detection and public opinion understanding.

3.2. Opinion simulation and biases

Large language models have shown new possibilities in public opinion simulation and public opinion prediction. Previous studies have shown that LLM can reproduce the distribution of public positions in political elections and policy discussions to a certain extent. For example, by making the model predict the political tendency of German voters, it is found that the overall trend of the results is consistent with the real survey to some extent, which shows the potential of LLM in opinion prediction [9]. Similarly, ChatGPT and other models can use huge corpus and context information to better simulate the trend of public opinion in the American context [10].

However, this kind of simulation still has significant limitations and deviations in practice. The first is the cultural and linguistic bias caused by the uneven distribution of corpus. At present, the training corpus of mainstream LLM mostly comes from the Internet texts and publications in the English world, which makes the model have high fitting and prediction accuracy when dealing with public opinions in the English context. However, when they are applied to non-English contexts such as German, Filipino or Bengali, they often perform distorted due to the lack of sufficient localization training data. For example, in the German election simulation, the model is good at reproducing the distribution of voters for mainstream parties (e.g., the CDU or the SPD), but struggles to capture the true support for non-traditional parties (e.g., the AfD). Similarly, in the analysis of social issues in the Philippines, the model may ignore the unique local political expression habits and cultural metaphors, thus underestimating the public opinion influence of

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specific groups. This over-reliance on the "mainstream context" easily leads to the lack of universality of the model in cross-language public opinion research.

Moreover, the generalization ability of LLMS when transferring across cultures and regions is still limited. Large language models show instability in multi-task and multi-context emotion simulation, especially in the prediction of irony, metaphor or complex social topics, often showing logical jumps or results deviation [7]. This shows that the application of LLM in public opinion simulation is still in the exploratory stage, and its results need to be combined with manual verification and multi-source data verification to provide more robust support for election prediction or policy research.

3.3. Event detection and narrative analysis of public opinion

In the research of public opinion, event detection and information activity analysis are the key links to understand the dynamics of public opinion. The introduction of LLM makes this process with a higher level of automation and intelligence. Firstly, LLM shows significant advantages in false information detection. Compared with traditional methods that rely on keywords or artificial rules, LLM can identify potential semantic anomalies and narrative inconsistencies from the context, to effectively find "hidden" false information. This ability is especially applicable to the fragmented and diverse textual content in the social media environment, which can help to quickly identify misleading statements and information manipulation behaviors.

Secondly, LLM also performs well in narrative frame identification. Researchers have applied LLM to political information parsing with the help of narrative frame theory and BEND framework. It can automatically identify typical operational strategies such as "topic incitement" and "narrative distortion" and classify them into specific narrative modes [11]. This process can help researchers understand the deep logic of information activities and reveal how different political forces influence public sentiment and policy direction by manipulating narratives.

LLM has also been proved to have application value in political communication analysis and policy research, and PolicyPulse system is a typical case. By integrating the discussion data of online communities such as Reddit and using LLM to classify opinions and extract emotions, the system can provide policy researchers with real-time insights into public opinions [10]. Compared with traditional interviews, questionnaires or manual retrieval, this approach was able to significantly shorten the time to obtain feedback and improve the coverage of multiple opinions.

LLMS provide multi-level support in public opinion event detection and information activity analysis: they can not only improve the accuracy of false information identification, but also reveal the operation mechanism of political narratives. By combining with social data platforms, LLMS can provide more real-time and detailed public opinion portraits for policy research and public governance. This method not only expands the depth of public opinion analysis, but also lays the foundation for constructing a more intelligent and auditable public opinion governance system in the future [12].

4. LLM-driven public opinion modeling and future prospects

4.1. Hybrid modeling methods for public opinion evolution

In the research of public opinion evolution, it is often difficult to take into account both macro propagation law and micro individual behavior by only relying on a single calculation method. In recent years, the composite modeling method combining LLM and traditional transmission

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dynamics model has gradually become a new research trend. The core idea is to use the natural language understanding and generation ability of LLM to describe the individual level opinion dynamics, and use the propagation dynamics equation or network model to simulate the diffusion process at the group level, so as to realize the multi-level evolution reconstruction of public opinion.

The Fusing Dynamics equation-LLM method is constructed by Fusing Dynamics Equation and LLM. In this framework, the role of opinion leader was played by LLM, and the evolution of opinion was constrained by Cellular Automata. The behavior of opinion followers is embedded in a dynamical system that combines CA and susceptitive-infection-Recovery model [1]. This design not only retains the macroscopic interpretability of the traditional equation model, but also improves the authenticity of language and emotion changes in the simulation by using the generation ability of LLM. Experimental results show that FDE-LLM performs better than pure ABM or single LLM simulation on multiple microblog real data sets, and effectively improves the accuracy and stability of public opinion evolution prediction.

In addition to FDE-LLM, previous studies have further explored the coupling modeling paradigm of LLM with a variety of propagation models. For example, the combination of LLM and CA model can describe the local interaction between individuals, and the formation of public opinion burst points, while the combination of LLM and SIR/SEIR model can help to capture the macroscopic evolution characteristics of public opinion propagation in the initiation, diffusion, climax and extinction stages. This kind of multi-level composite framework makes the micro emotional interaction and macro diffusion law can be co-modeled in a unified system, so as to make up for the explanation limitations of a single model. Compared with traditional ABM, LLM-driven simulation has more advantages in natural language understanding and complex semantic generation, but ABM still maintains key values in structural transparency and causal interpretability [13]. Therefore, the current research trend is not to replace ABM, but to realize complementation through fusion modeling, so as to build a more realistic, interpretable and verifiable simulation system of public opinion evolution.

4.2. Challenges and future directions

Although large Language models have shown significant potential in public opinion analysis and evolution research, their application still faces multiple challenges. Firstly, the problem of bias and fairness is particularly prominent. Limited by the training corpus mainly in English context and mainstream media, LLM often implies cultural and ideological bias, and its ability to depict minority groups and marginalized views is insufficient, which may affect the objectivity of public opinion judgment and the reliability of governance decisions. Secondly, there are still obvious deficiencies in cross-language and cross-cultural adaptability. Previous studies have shown that the performance of the model is relatively stable in the English environment, but its performance significantly decreases in multilingual scenes such as German and Filipino, which is difficult to effectively capture the characteristics of non-mainstream political discourse [14], limiting its global applicability.

In addition, the abruptness and dynamics of public opinion evolution put forward higher requirements for the real-time response ability of the model [15]. The traditional static training paradigm is difficult to reflect the rapidly changing hot topics in social media in time, resulting in prediction lag. Future research is urgently needed to explore an adaptive update mechanism that combines LLM with real-time data streams to support dynamic tracking and prediction. At the application level, the interpretability and transparency of the model also need to be improved. The current LLM mostly outputs results in a black-box manner, and the combination of chain of thought

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hints and interpretable AI methods is expected to enhance the auditability of the reasoning process and the credibility of the conclusion.

In general, the positioning of LLM in public opinion governance should be an enhancement tool rather than a replacement for human experts. Future research can be carried out from five aspects: debiasing and fairness constraints, multilingual and cross-cultural corpus construction, real-time data fusion, interpretability methods, and human-computer collaboration mechanisms, to build a more reliable, interpretable, and socially acceptable framework for public opinion analysis and evolution.

5. Conclusion

LLM is reshaping the technical path of public opinion analysis and evolution research. Its cross-lingual and few-shot capabilities in sentiment and opinion recognition make more fine-grained public stance characterization possible and provide new tools for fake reviews and narrative identification. In terms of public opinion simulation and prediction, LLM shows the potential to depict the evolution of public opinion, but its results are still restricted by factors such as corpus bias, ideological orientation and insufficient cross-cultural adaptability. In the event detection and information activity analysis, the related applications have preliminarily verified the practical value of LLM in policy research and political communication analysis. In general, LLM is still difficult to be used as an independent solution for public opinion analysis. Its core value lies in deep integration with communication dynamics models and agent-based methods, and functioning under the framework of interpretability, human-computer collaboration and fairness constraints. Future research should further improve the reliability and generalization ability of the model to support more scientific and robust public opinion evolution analysis and governance decision-making.

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