# Investigating Large Language Models in Sentiment Analysis: Techniques, Trends, and Challenges

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**Abstract:** This paper provides an overview of a literature review for large language models (LLM) that provides a description of each step in the social sentiment analysis pipeline from data collection to actionable insights. This literature review also reveals the value of transformer-based models such as BERT and GPT to assist with the efficient processing of natural language data and performing more complex sentiment analysis types. Within the framework of this literature review, various components will also be discussed including the classification of sentiment, detection of emotion, and extraction of topics to assist in gaining more insight into how LLMs can assist with deeper understanding of user behaviour, emotion, and opinion. Within the literature review, there has also been an identification of trends and patterns that have emerged as a result of existing research that indicate public mood and perception across different domains. Major challenges such as ethical concerns, model biases or errors, and transparency and accountability are also presented in this literature review. Finally, conclusions and recommendations are provided for improving the performance of LLM sentiment analysis and reducing bias, as well providing future directions for further research regarding LLM-inspired sentiment analysis.

**Keywords**: Natural Language Processing; Transfer Learning; Large Language Models; Generative Pre-Trained Transformer; Bidirectional Encoder Representation Transformer

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## Introduction

As a result of rapid developments in digital technologies, many organizations have become dependent on the use of large amounts of online data in order to gain insight into how users feel, what they like and dislike, and what their behaviours are. Sentiment analysis is a major task in natural language processing and consists of the automatic extraction of subjective information from text data [1]. As such, it is an important component of the data-driven decision-making process in today's business world. In particular, product-based companies use sentiment analysis to assess and manage customer feedback about their products and services as well as to continually improve products and build customer goodwill [2]. The digital environment contains large volumes of information that users create, which are posted to various websites (e-commerce, social media, blogs, and forums). For example, there are millions of reviews of products and services available on platforms such as Twitter and Amazon that demonstrate what people think about the products or services being reviewed [3]. Companies that collect and analyze this data are able to respond quickly and effectively to customer complaints, improve their marketing efforts, and increase overall customer satisfaction. In addition, sentiment analysis provides valuable support to many different types of professionals (business, marketing, sports, and politics) who use it to make informed decisions based on the opinions of their customers [4]. Figure 1 presents the summarize view of the presents the contribution of the work.The immense growth of data volume and type has created tremendous obstacles. A large percentage of online data is unstructured, often multilingual, and contains colloquial language with informal phrases, idioms, and specialized vocabulary [5]. Current approaches to sentiment analysis take advantage of lexicons and machine learning techniques, but these systems are not well-equipped to deal with the complexity of many forms used in this type of communication. The challenges faced by these methods establish the need for more complex, scalable, and contextualized solutions. Recent developments in large language models (LLMs), especially of the transformer variants (e.g. BERT and GPT) have progressed rapidly in their ability to perform well at sentiment analysis tasks compared to traditional methods.

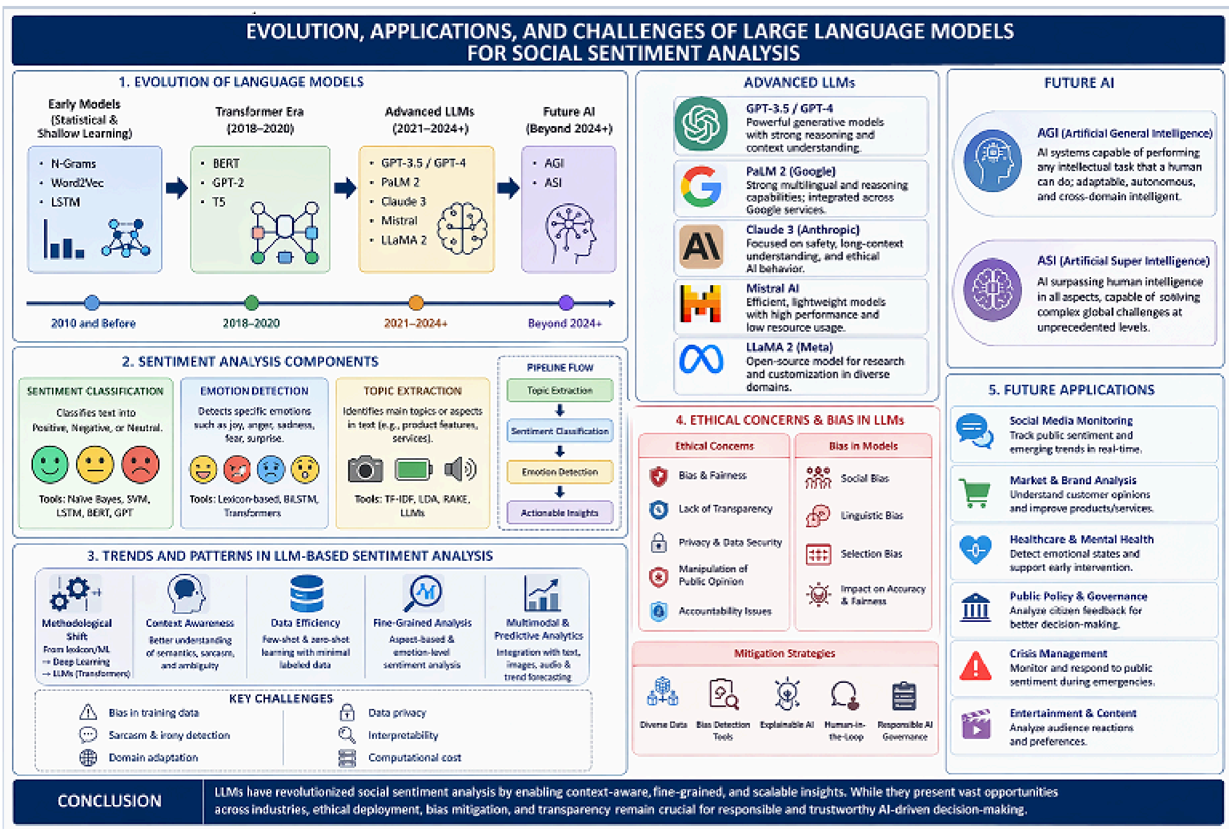


*Figure 1. Contribution of the presented Review Work*

The deep contextual understanding capabilities of LLMs and their training on such relatively large amounts of text provide LLMs with superior abilities to address ambiguity in language use (e.g., expressions used to indicate sarcasm) and making them significantly better at being able to adapt to domain-specific language than traditional methods [6].

The purpose of this survey is to provide an overview on the various techniques of sentiment analysis, the focus of which will be on LLM-based approaches. Additionally, the report will summarize the key elements of traditional and contemporary techniques; addresses the various datasets and applications used for each; discuss the major challenges and emerging trends associated with sentiment analysis.

### Trends and Patterns

The emergence of Large Language Models (LLMs) has significantly transformed sentiment analysis, particularly in terms of evolving trends and patterns observed in existing research. One of the most notable trends is the clear methodological shift from traditional approaches to advanced transformer-based architectures. Figure 2 visualizes the trend patterns of sentiment analysis.

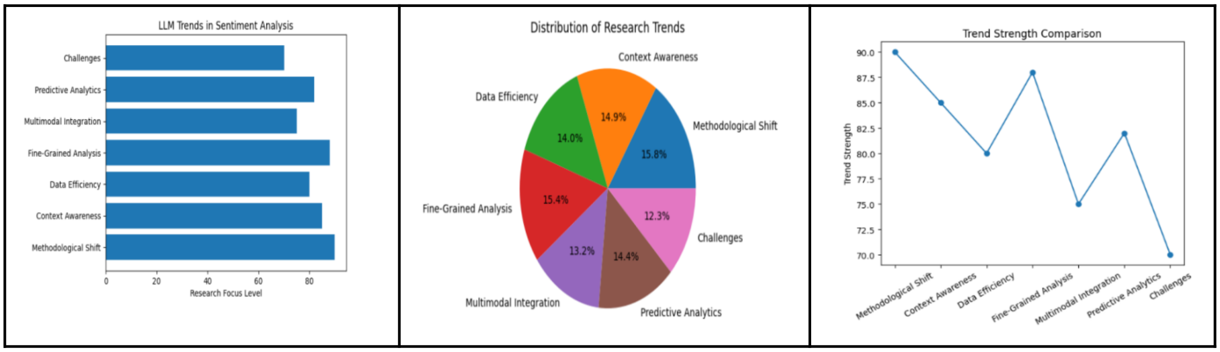


*Figure 2. Trend Patterns of Sentiment Analysis*

In conclusion, the implications of LLMs for sentiment analysis, particularly in terms of trends and patterns, demonstrate a clear evolution toward more advanced, context-aware, and predictive systems.

### Implication and Challenges

Bias in Large Language Models (LLMs) is one of the most critical challenges affecting the reliability of social sentiment analysis. These models are trained on massive datasets collected from the internet, which often contain historical, cultural, and social biases. As a result, LLMs may unintentionally learn and reproduce these biases while analyzing sentiment, leading to skewed or unfair outcomes. Bias in LLMs can take multiple forms. Social bias arises when models favor or disadvantage particular demographic groups (e.g., gender, race, or region). Linguistic bias occurs when certain dialects, slang, or non-standard language patterns are misinterpreted, often leading to incorrect sentiment classification. Additionally, selection bias in training data can cause overrepresentation of certain opinions, making the model less generalizable across diverse populations. Bias directly affects the accuracy and fairness of sentiment predictions. For instance, posts written in informal language or by minority communities may be incorrectly classified as negative. Similarly, topics related to sensitive social issues may receive biased sentiment scores, distorting the true public opinion. This can have serious consequences in domains like politics, marketing, and public policy, where sentiment analysis is used for decision-making [7].

### Future Applications

Rapid advances in Large Language Models have led sentiment analysis to grow from a basic polarity measurement (i.e., positive/negative/neutural) into more intelligent, context-aware and predictive systems. The focus of future sentiment analysis tools will be to improve understanding of human emotions and improve real-time, data-driven decision making across all industries.

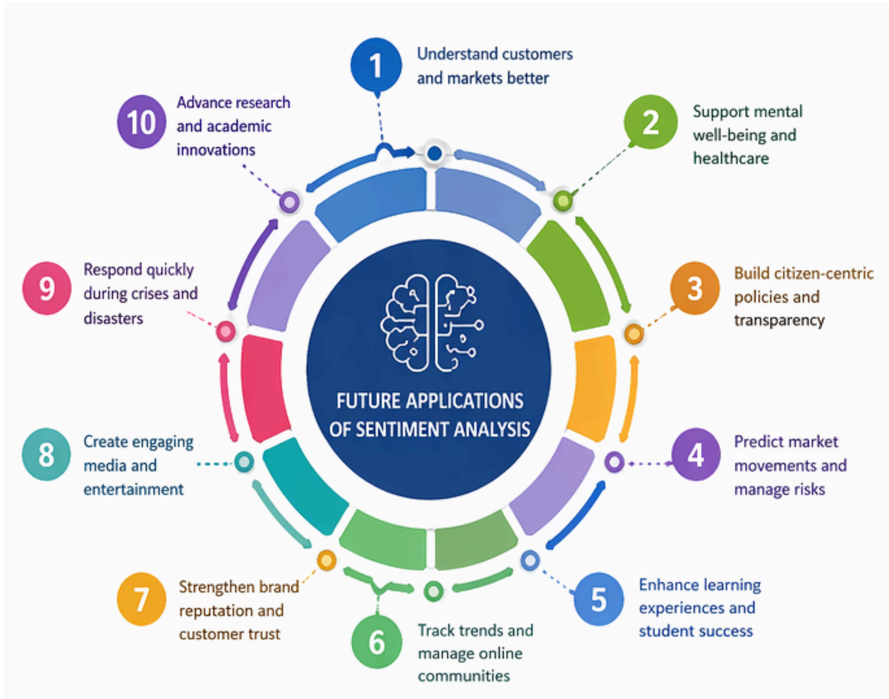


*Figure 3. Future Requirements and Applications of Sentiment Analysis*

Figure 3 presents the future applications of sentiment analysis. Governments may utilize sentiment analysis within public policy and governance as a means of gaining insight into citizen support, sentiment and opinion around various issues including policies and services provided, as well as providing for more transparency in the decision-making process; ultimately, this will facilitate the development of policies and services that better respond to citizen need and demand (citizen-centric) [8].

**Conclusion and Future Work**

The presented review demonstrates the significant role of Large Language Models (LLMs) in advancing social sentiment analysis, beginning with large-scale data collection from social media platforms, news sources, and online forums. By leveraging powerful models such as BERT and GPT, the framework enables sophisticated sentiment processing through techniques like sentiment classification, emotion detection, and topic extraction. These capabilities allow researchers and organizations to gain deeper insights into trends, public opinion, and overall societal mood, supporting informed decision-making across domains such as marketing, governance, and public policy. To address these limitations, future work should prioritize the development of bias-aware and explainable LLMs trained on diverse and representative datasets. Incorporating multimodal sentiment analysis, which includes text, images, and videos, can enhance contextual understanding. Furthermore, domain-specific fine-tuning and human-in-the-loop approaches can improve accuracy and reliability. Establishing ethical AI frameworks and integrating adaptive learning mechanisms will be essential for ensuring transparent, fair, and context-aware sentiment analysis in rapidly evolving social environments.

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