JeDEM 17(3): 59-77, 2025
ISSN 2075-9517
http://www.jedem.org
Date of submission: 05.06.2025
Date of acceptance: 15.09.2025
Article DOI: 10.29379/jedem.v17i3.1069

Harnessing sentiment analysis for political campaigns: Trends, platforms, and future directions

Kapil Gurung

ORCID: 0000-0002-1534-977X
College of Global AI Convergence, Seoul Christian University, Seoul, South Korea
kapilgurung@scu.ac.kr

Abstract: This reflection examines the role of social media engagement in predicting voter support through a comprehensive review of studies on sentiment analysis in political campaigns from 2010 to 2025. Synthesizing studies across diverse contexts (e.g., U.S., Europe, India, Indonesia) and platforms (e.g., Facebook, Twitter/X, TikTok, Reddit), this reflection identifies six key thematic clusters: proxy for voter sentiment, platform dynamics, technical advances, methodological and ethical issues, polarization, and campaign implications. This reflection highlights key turning points, such as the shift from Twitter-centric approaches to multi-platform analytics, the rise of deep learning, and the emergence of ethical criteria. The future work proposes a Voter Sentiment Index (VSI) as a standardized, cross-platform metric to improve interpretability and ethical application, ensuring robust and responsible use in political forecasting and governance.

Keywords: Political campaign, Sentiment analysis, Social media platforms, Voter behavior

1. Introduction

In the last fifteen years, sentiment analysis has become a vital tool in understanding political behavior, public opinion, and campaign dynamics within digital spaces. With the global use of social media platforms such as Twitter (now X), YouTube, TikTok, Facebook, Instagram, and Reddit, political engagement has increasingly migrated online, creating vast, real-time datasets that can be analyzed to infer voter sentiment. This shift has given rise to a new research frontier by positioning sentiment analysis as not just a technical tool but also a sociopolitical lens for interpreting digital democracy.

Initially, early studies focused primarily on Twitter metrics, such as mentioning counts and hashtag frequencies, as proxies for electoral outcomes. However, subsequent research has revealed the limitations of such approaches, ranging from data noise, platform-specific biases, and echo chamber effects to ethical concerns about surveillance and manipulation (Ceron, Curini, Iacus, & Porro, 2014; Gaur & Yadav, 2025; Metaxas, Mustafaraj, & Gayo-Avello, 2011). Over time, the field

has matured, incorporating deep learning models, multi-platform data integration, cross-lingual sentiment classification, and nuanced methodological frameworks that account for temporal, emotional, and sociocultural factors.

Recent studies have expanded beyond single-platform prediction to encompass the structural and cultural nuances of different platforms, revealing that each medium, whether X, YouTube, Facebook, or TikTok, produces distinct forms of emotional, ideological, and demographic expression. Moreover, scholars have increasingly contextualized sentiment not merely as a numerical score, but as a product of framing, polarization, and algorithmic visibility (Bermingham et al., 2013; Brito, Silva Filho, & Adeodato, 2024; Valle-Cruz, Sandoval-Almazán, López-Chau, & Criado, 2024). Sentiment analysis is no longer about what people feel only, but how, where, and why that feeling is expressed and what it means for electoral behavior and democratic governance.

This evolving methodological landscape has opened new possibilities but also introduced new challenges. Despite technical advances, key concerns persist over reliance on black-box models, limited platform diversity, underexplored connections between digital sentiment and offline political behavior, and insufficient safeguards for ethical data use in politically sensitive environments. These gaps suggest a critical need to assess not only how sentiment is measured but also how it is conceptualized, interpreted, and applied in real-world political campaigns.

To address this gap, this reflection poses the following central research question: How has sentiment analysis been applied to political campaigns between 2010 and 2025, and what thematic, methodological, and ethical patterns emerge from the literature?

This reflection aims to provide a timely and comprehensive reflection on the role of sentiment analysis in political campaigns over the past fifteen years. By synthesizing fifty-seven selected studies across multiple platforms (X, YouTube, Facebook, Instagram, TikTok, Reddit), I identify six key thematic clusters: (1) social media engagement as a proxy for voter sentiment, (2) platform-specific sentiment dynamics, (3) technological and methodological advancements, (4) ethical considerations, (5) polarization and echo chambers, and (6) applications in campaign strategy and digital governance. Additionally, proposing Future research direction for building robust, transparent, and socially grounded sentiment analysis systems in the political campaign context.

The remainder of this reflection is organized as follows. The second section presents the research method and analysis, detailing the research design and the criteria used to select and examine the relevant literature. The third section outlines future research agendas, emphasizing the importance of developing cross-platform modeling frameworks, establishing robust ethical guidelines, and incorporating behavioral validation to strengthen the reliability and social relevance of sentiment analysis in political campaigns.

2. Framing studies on sentiment analysis during political campaigns

A total of eighty-nine articles published between 2010 and April 2025 were collected. Using criteria focused on sentiment analysis in political campaigns, fifty-seven articles were selected for in-depth analysis. To address the central research question, I conducted a comprehensive literature review

and documentary analysis. This process led to the identification of six distinct research clusters. Each thematic group was examined with reference to the entire citation sample to establish the main areas of focus within the field and their interrelated approaches. Additionally, excluded articles were reviewed to assess their potential relevance and synergy with sentiment analysis in political research.

Based on the analysis, I categorized the core research topics, which are summarized in Table 1

Table 1. Main themes and key insights

Themes	**No. of Studies**	**Key Insights and Representative Studies**
Social Media Engagement as a Proxy for Voter Sentiment	11	Early claims of Twitter as a morro for elections (Tumasjan, Sprenger, Sandner, & Welpe, 2010); multi-platform proxies in recent contexts (Alnsour, Alsharo, AL-Essa, & Smerat, 2025; Gutierrez, De León, Zareei, & dos Santos, 2024).
Dynamics in Sentiment Analysis	9	Platform-specific influences, e.g., Facebook reactions (Robertson, 2011); critiques of single platform limits (Brito et al., 2024).
Advancements	10	From lexicons to LLMs (Faria et al., 2024; Turney, 2013), deep learning benchmarks (Nakov et al., 2016).
Methodological and Ethical Considerations	11	Critiques of methodological Flaws (Metaxas et al., 2011); ethical data challenges(Gupta, Verma, & Kapoor, 2024; Odegbile & Oyelami, 2024).
Polarization and Echo Chambers	8	Partisan skews (Valle-Cruz et al., 2024; Wong, Tan, Sen, & Chiang, 2016); amplification in elections (Yates, Mentzer, & Tousignant, 2024)
Political Campaigns and Digital Governance	8	Strategy shaping (Kumari & Singh, 2024; Razzaq, Qamar, & Bilal, 2014); governance implication (Gaur & Yadav, 2025)

Note: for a detailed catalog of all studies, see Appendix A.

2.1. Social media engagement as a proxy for voter sentiment

I observe that social media engagement serves as a dynamic, context-sensitive proxy for voter sentiment, evolving from simple volume metrics to sophisticated multi-platform analyses. Early studies by Tumasjan et al. (2010) claimed Twitter's 100,000 tweets mirrored the 2009 German election, sparking debate about digital engagement's predictive power. However, critiques around 2013-2014 marked a turning point, highlighting biases in Twitter-centric approaches, prompting granular, event-based modeling (Unankard, Li, Sharaf, Zhong, & Li, 2014). Subsequent studies expanded to diverse contexts: Boutet, Kim, and Yoneki (2013) inferred UK election support via tweet volume,

Monti et al. (2013) modeled Italian voter disaffection, and Bovet and Makse (2019) mapped U.S. election polarization through retweet networks.

Recent advancement embraces multi-platform data. Wang, Sundar, and Ram (2024) analyzed 830,000 tweet cascades to predict U.S. Senate outcomes, while Firdaus, Yudhana, and Riadi (2024) tracked pre-election sentiment flows. Beyond Twitter, Purwandari, Jiwanggi, and Yulianti (2024) achieved a 6.92% vote-share prediction error using YouTube comments for Indonesia's election, Samosir and Riyaldi (2024) extracted your sentiment from TikTok, and Alnsour et al. (2025) revealed regional contrasts via 25,000 Reddit posts for the 2024 U.S. election. Gutierrez et al. (2024) fused Instagram and YouTube data to enhance accuracy in Mexico's elections, recognizing each platform's unique demographic and emotional registers: Twitter captures real-time reaction (Tripathi & Neelakantappa, 2024), YouTube offers depth (Ma'Aly, Pramesti, & Fakhrurroja, 2024), Facebook distills emotions (Alashri et al., 2016; Robertson, 2011), and TikTok, Instagram, and Reddit add cultural nuance.

Key Insights emphasize triangulating data across platforms to mitigate algorithmic biases and vocal minority distortions, as a single-source proxy often misrepresents sentiment (Metaxas et al., 2011). While platforms like Instagram thrive on influencer signaling and YouTube on deliberative discourse, raw engagement requires contextualization to avoid overemphasizing extremes. This evolution from Twitter-centric counts to multi-platform, deep-learning classifiers offers unparalleled insight into the real-time pulse of political publics, when provided data is carefully contextualized and triangulated.

2.2. Platform-specific dynamics in sentiment analysis

The reflection reveals that platform-specific dynamics profoundly shape sentiment expression, necessitating tailored approaches to capture political sentiment accurately, particularly after the post-2016 rise of multimodal data. Each platform's unique affordances, such as Twitter/X's brevity for rapid reactions (Stieglitz & Dang-Xuan, 2013; M. K. Tripathi & Neelakantappa, 2024), Facebook's structured reactions for clear emotional signals (Alashri et al., 2016; Robertson, 2011), Instagram and TikTok's visual and meme-driven content (Samosir & Riyaldi, 2024; Santana, Santana, Sampaio, & Brito, 2024), and Reddit's threaded discussions for complex narratives require distinct analytical models to reflect their sociotechnical ecosystems(Alnsour et al., 2025). X excels in real-time tracking of political events, such as debates or crises, but its 280-character limit introduces noise from sarcasm, bots, and limited context (Bermingham et al., 2013). YouTube's longer-form comments enable deeper emotional insights, with Bi-LSTM (Bidirectional Long Short-Term Memory) models achieving 98% accuracy in classifying tones like "disgust" or "trust" (Ma'aly, Pramesti, Fathurahman, & Fakhrurroja, 2024) and engagement metrics predicting Indonesian election outcomes with a 6.92% error margin (Purwandari et al., 2024). Facebook's reaction system simplified emotional aggregation but constrained nuance (Upreti, Pokhrel, Ban, & Gurung, 2025). Instagram and TikTok are reliant on visual and influencer culture, demanding innovative NLP (Natural Language Processing) for audiovisual cues, memes, and slang, while Reddit's community-driven discussions reveal sustained public reasoning and regional contrasts.

Essential findings highlight the pitfalls of mono-platform analyses (Brito et al., 2024), as each platform captures distinct demographics and emotional registers: X tracks rapid shifts (Boutet et al., 2013), YouTube offers deliberative depth, and Facebook distills quantifiable emotions. Fusing data from Instagram and YouTube improves predictive accuracy as seen in Mexican election forecasts (Gutierrez et al., 2024). However, platform-specific biases such as X's amplification of vocal minorities (Trachanas, Valavani, Alexandris, & Giannakis, 2024), algorithmic curation, or demographic skew persist, necessitating methodical triangulation across platforms and a contextual filter to mitigate distortion. This shift from Twitter-centric studies in the early 2010s to nuanced, multi-platform approaches in 2025 highlights that understanding platform dynamics is crucial for decoding digital democracy.

2.3. Advancement in sentiment analysis and election

This reflection traces a technological arc in sentiment analysis for elections, from basic keyword matching (He, 2012; Tumasjan et al., 2010) to sophisticated transformer LLMs (Large Language Model) (Faria et al., 2024; Mishra, Punia, Sikka, Sharma, & Sikka, 2024). Early methods critiqued for lacking semantic depth (Metaxas et al., 2011) spurred refinements (He, 2012), sentiment quantification, and emotion lexicons (Turney, 2013), which captured nuanced political effect. Mohammad, Dorr, Hirst, and Turney (2013) featured this with psychological lexicons, while Burnap, Avis, and Rana (2013) introduced the COSMOS (Cardiff Online Social Media Observatory) platform. A pivotal moment came with SemEval (Semantic Evaluation) benchmarks (Nakov et al., 2016), standardizing X sentiment evaluation and enabling forecasting frameworks (Liu, Yao, Guo, & Wei, 2021).

Post-2016, transformer models and regional adaptations boosted accuracy: Mishra et al. (2024) achieved a 1.345 mean absolute error for India's 2019 election using BERT (Bidirectional Encoder Representations from Transformers), Tanaja, Widjaya, Gunawan, and Setiawan (2024) reached 84.7% with Indo-BERT, and Faria et al. (2024) hit 96.33% with Gemini 1.5 pro for Bengali tweets. Platform-specific advances, like 98% accuracy on YouTube comments via Bi-LSTM (Ma'Aly, Pramesti, & Fakhrurroja, 2024), and a regional model for Nigeria (Agagu & Gbadebo, 2024), highlight scalability. Cross-platform suspension, as in Gutiérrez, Zareei, de León Languré, and Brito's (2024) prediction of Mexico's 2024 election and Kumari and Singh's (2024) 87.65% accurate LSTM model across X, YouTube, and Facebook, underscores the value of multi-source approaches (Brito et al., 2024)

Core takeaway reveals that while accuracy soared, interpretability lags, risking overreliance on a black-box model (Ma'aly, Pramesti, Fathurahman, et al., 2024). Cross-platform adaptations (Tanaja et al., 2024) and regional fine-tuning (Agagu & Gbadebo, 2024) demonstrate scalability, yet blending human insight with AI remains essential for context-aware forecasting. This evolution from lexicons to LLMs and multi-platform architectures positions sentiment analysis as a sociotechnical strategy, merging linguistic nuance, political insight, and machine learning for robust election forecasting.

2.4. Methodological and ethical considerations

The analysis highlights persistent methodological and ethical challenges in sentiment analysis for electoral prediction, including data noise, user bias, interpretive ambiguity, and ethical data use (Gaur & Yadav, 2025). Foundational critiques (Metaxas et al., 2011) exposed flaws in early Twitter-based predictions, questioning the equation of engagement volume with voter intent, a concern later echoed by Demartini (2011) for log-based analyses. These critiques evolved into calls for transparency and methodological rigor (Ceron et al., 2014; Nakov et al., 2016), emphasizing that results vary with model tuning, time windows, and user demographics. Platform-specific biases further complicate representation: X amplifies vocal minorities, often skewed toward younger or extreme users (Tripathi & Neelakantappa, 2024), while Peruvian tweets challenge accurate labeling due to sarcasm and cultural idioms (Cedano, Picon, & Ticona, 2024). OCR (Optical Character Recognition) error in German-language posts with regional dialects or non-standard typography, and further complexity (Hellwig, Fehle, Bink, Schmidt, & Wolff, 2024).

Engagement metrics introduce interpretive ambiguity. Retweets may signal endorsement or ridicule (Mustafaraj & Metaxas, 2011), YouTube's "dislike" button may reflect disapproval of content or identity (Ma'aly, Pramesti, Fathurahman, et al., 2024), and Facebook's "Sad" reaction can denote sympathy, grief, or protest (Robertson, 2011). Bermingham et al. (2013) noted Twitter's 280-character limit produces shallow emotional cues, and Gaur and Yadav (2025) described large-scale social media data as inherently "skewed and nosy." Advanced models, like Argandoña-Mamani, Ormeño-Alarcón, Iparraguirre-Villanueva, Paulino-Moreno, and Cabanillas-Carbonell's(2023) 97% accurate Random Forests, prioritize prediction over interpretability, risking false precision in minority dialects, sarcasm, or underrepresented regions.

Primary outcome emphasizes that high accuracy must pair with ethical protocols to address privacy and consent issues in large datasets, such as 364,867 Nigerian tweets (Odegbile & Oyelami, 2024), or 2 million Trump-related posts (Albanese, Feuerstein, & Balenzuela, 2024), or Facebook reactions without consent (Alashri et al., 2016), which raises privacy and consent issues, particularly for vulnerable groups like minors on Instagram (Santana et al., 2024). Neuromarketing techniques exploiting sentiment spike on X (Yaqub, Chun, Atluri, & Vaidya, 2017) or YouTube trends (Qorib, Gizaw, & Kim, 2023) blur the line between analysis and manipulation (Gupta et al., 2024). As sentiment analysis advances with cross-platform data and neural networks, adopting transparent ethical frameworks, contextual validation, and inclusive methodologies is critical to safeguard democratic integrity.

2.5. The role of polarization and eco chambers

This analysis reveals that political polarization and echo chambers significantly distort social media sentiment, challenging its reliability as a proxy for voter behavior. Yates et al. (2024) show X's polarized discourse in the 2022 U.S. Senate race, where vocal partisan minorities overshadowed silent majorities, creating a misleading consensus. Similarly, X polarization in elections (Valle-Cruz et al., 2024) highlights how platforms reinforce divisions, urging democratically weighted analysis to reflect the true public opinion. Srinivasa (2024) notes that echo chambers skewed U.S. election sentiment, while Trachanas et al. (2024) observed amplified extremes in Greek elections. Earlier, Wont et

asl (2016) quantified partisan asymmetries on X, with Albanese et al. (2024) showing intensified ideological fragmentation in the 2024 U.S. campaign, driven by algorithms prioritizing divisive content.

Psychological effects worsen these dynamics. Monti 2013 modeled Italian disaffection, revealing susceptibility to echo chambers, while Wang et al. (2024) identified bandwagon effects creating illusory candidate momentum. Platform architectures amplify this: X fosters ideological in-groups (Yates et al., 2024), and Facebook's reactions fuel affective polarization (Alashri et al., 2016). Political campaigns exploit these divisions, micro-targeting homogeneous groups in India (Singhal, Sood, Kaushal, Gehlot, & Rana, 2023) and Indonesia (Atmojo, Arienaldi, Edbert, & Aulia, 2024), intensifying fragmentation and complicating real-team sentiment modeling (Oikonomou & Tjortjis, 2018).

Critical observations highlight methodological challenges: polarized data risks overfitting to extremes, underrepresenting moderate (Brito et al., 2024). Multi-platform, demographically contextualized approaches are essential to correct these distortions. Polarization is both a sociopolitical issue and a technical flaw that distorts inputs and biases interpretations, threatening digital democracy's inclusiveness. From Monti et al.'s (2013) early disaffection model to Valle-Cruz et al.'s (2024) polarization analysis, echo chambers emerge as a defining feature, requiring robust, accountable sentiment analysis systems to ensure accurate and fair electoral forecasting.

2.6. Implications for political campaigns and digital governance

The analysis demonstrates that sentiment analysis has evolved from academic inquiry to a pivotal tool for political campaigns and digital governance, enabling precise, responsive strategies while posing ethical risks. Sentiment informs campaign strategies (Kumari & Singh, 2024), as seen in Modi's X-driven messaging adjustments and Razzaq et al.'s (2014) real-time outreach in Pakistan. Singhal et al. (2023) showed that emotionally resonant posts on X boosted engagement, while Sutrisno et al. (2024) noted 65% of Indonesian debate content used symbolic language, guiding visual strategies on YouTube and TikTok (Samosir & Riyaldi, 2024). Multi-platform approaches enhance effectiveness: Gutierrez et al. (2024) fused Instagram and YouTube data to predict Mexico's 2024 election, and Alashri et al. (2016) used Facebook reactions as sentiment indicators.

In governance, sentiment analysis shifts from prediction to responsive tools (Rahman & Suarga, 2024), with X shaping Southeast Asian civic discourse and NLP tools extracting policy themes (M. Tripathi, Moorthy, & Nemade, 2024). Hellwig et al. (2024) mapped X discussions on climate and immigration to inform agenda-setting, while TikTok's 92.1% accurate sentiment classification, Samosir and Riyaldi (2024) highlight its role in tracking youth sentiment, linking to increased participation via social media (Barati, 2023). This highlights sentiment's role in bridging online-offline engagement for inclusive democracy.

Essential findings stress that multi-platform integration improves campaign and governance outcomes (Gutierrez et al., 2024) but requires ethical oversight to prevent manipulation (Gaur & Yadav, 2025). Bermingham et al. (2013) cautioned against oversimplifying public opinion, and Argandoña-Mamani et al.'s (2023) 97% accurate Random foresight models highlight the need for interpretable tools in public-facing applications. From Razzaq et al.'s (2014) early applications to Gutiérrez et al.'s

(2024) neural models, Sentiment analysis offers opportunities to connect campaigns, adapt governance, and amplify voice, but demands transparency, contextual sensitivity, and inclusive design to avoid bias and ensure democracy integrity.

3. Considerations for future agendas

The synthesis of fifty-seven key studies reveals a maturing yet uneven field: technologically advanced, but methodologically and ethically complex. As the digital ecosystem evolves, so must the analytical paradigms used to interpret political sentiment. Building upon the identified research clusters - social media engagement, platform dynamics, methodological innovations, ethical considerations, polarization, and campaign application- several priorities for future agendas emerge.

A priority is the integration of platforms and contexts. I advocate for cross-platform frameworks to address demographic biases, emotional registers, and platform-specific affordances, moving beyond X-centric research to include Reddit, Instagram, TikTok, and region-specific platforms. Expanding to underrepresented regions like South Asia, Latin America, and Africa (Matloga, Marivate, & Olaleye, 2025) ensures global validity and cultural adaptability.

Another key direction lies in balancing predictive accuracy with interpretability. While deep learning and transformer-based models have dramatically advanced performance, their opacity remains problematic in politically sensitive domains. Greater emphasis should be placed on interpretable and explanatory approaches, including hybrid models that combine symbolic reasoning, rule-based NLP, and neural classifiers. These can offer both predictive power and insight into the socio-political narratives underpinning digital expression.

Polarization and echo chambers present an ongoing challenge as online discourse often amplifies partisan minorities. Researchers must develop corrective strategies that reweigh overrepresented extremes, incorporate demographically balanced samples, and calibrate sentiment across platforms. Such approaches reduce distortion and ensure that sentiment measures reflect a wider spectrum of public opinion rather than the amplification of extremes.

Ethical concerns also require systematic attention. Issues of privacy, consent, data ownership, and manipulation should be embedded into research design through protocols such as bias audits, impact assessments, and human-in-the-loop validation. Ethical protocols should also connect to accountability, extending beyond privacy to emphasize transparency and responsibility in practice (Agbesi, Budurushi, Dalela, & Kulyk, 2024; Kenosi, Zlotnikova, & Sigwele, 2024). At a broader level, institutional guidelines and international standards are necessary to govern sentiment analysis in political contexts, particularly where vulnerable groups or authoritarian settings heighten the risks of misuse.

Future work should also focus on temporal and longitudinal analysis. Political sentiment is not static but evolves in response to debates, scandals, crises, and campaign milestones. Incorporating temporal modeling, dynamic topic analysis, and sentiment drift detection can capture these dynamics and provide deeper insight into political momentum and voter volatility. Additionally, exploring ties to digital democracy, computational governance, and algorithmic public opinion will strengthen

the field by assessing AI's role in direct democracy and leveraging Fourth Industrial Revolution (4IR) technologies for transparent e-governance, ensuring alignment with democratic outcomes (Roskoshnyi, 2024).

Equally vital is the need to link digital signals to offline democratic behavior. Sentiment analysis must move beyond interpreting likes, retweets, or reactions and demonstrate connections to real-world outcomes such as vote choice, protest participation, or policy support. Mixed-methods validation- drawing on surveys, interviews, and electoral data-can provide the evidence base needed to ground digital proxies in democratic realities.

As governments increasingly explore sentiment tools for policy feedback, research should also assess which models are genuinely fit for public-sector use. Lightweight, explainable, and locally adaptable approaches may prove more effective than opaque deep-learning systems in civic settings that demand transparency. Testing such models in live environments such as smart city dashboards or participatory budgeting platforms could help identify their strengths and limitations.

Finally, the development of a Voter Sentiment Index (VSI) represents a promising step forward. Similar to economic confidence indices, a standardized, cross-platform measure could offer governments, campaigns, and civil society a common benchmark for interpreting public mood. Establishing such an index would require shared datasets and evaluation protocols, tailored to electoral and multilingual contexts.

These directions highlight that the goal is not merely to improve election forecasting, but to advance a reflective understanding of how digital publics express, contextualize, and reshape democracy through sentiment. Future research must therefore combine technical innovation with normative commitments to transparency, accountability, and inclusiveness.

4. Conclusion

This reflection reveals how sentiment analysis has become integral to political campaigns, evolving from early keyword counts to sophisticated, cross-platform applications powered by deep learning and large language models. Yet, persistent challenges like bias echo chambers, ethical data use, and interpretive ambiguity highlight that sentiment analysis is not merely computational but a societal practice demanding transparency, accountability, and inclusivity.

Situating these findings with JeDEM's focus on digital democracy, this reflection connects to earlier contributions, such as work on sentiment analysis in local government analysis (Matloga et al., 2025), studies of political polarization on X (Valle-Cruz et al., 2024), and youth political participation (Barati, 2023) in digital democracy. These studies highlight sentiment's role in bridging online-offline engagement, shaping both electoral strategies and responsive governance.

This reflection acknowledges limitations, including reliance on a subset of fifty-seven out of eighty-nine English-language, peer-reviewed studies and subject thematic categorization without quantitative meta-analysis or transparent coding protocols. The rapidly evolving social media and

AI landscape may further shift methodological and ethical considerations. These limitations highlight opportunities for refining sentiment analysis to better serve digital democracy. By aligning with JeDEM's mission, this reflection positions sentiment analysis as a bridge between technology and democratic vitality, emphasizing its potential and ethical challenges in reshaping twenty-first-century publics.

References

Agagu, M., & Gbadebo, S. D. (2024). *A Web-based Sentiment Analyzer for Tweets Using Machine Learning Techniques.* Proceedings of the 2024 International Conference on Science, Engineering, and Business for Driving Sustainable Development Goals (SEB4SDG). DOI:10.1109/SEB4SDG60871.2024.10629907

Agbesi, S., Budurushi, J., Dalela, A., & Kulyk, O. (2024). *Investigating transparency dimensions for internet voting*. eJournal of eDemocracy & Open Government, 16(3). DOI:10.29379/jedem.v16i3.916

Alashri, S., Kandala, S. S., Bajaj, V., Ravi, R., Smith, K. L., & Desouza, K. C. (2016). An analysis of sentiments on Facebook during the 2016 US presidential election. Proceedings of the 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM). DOI:10.1109/ASONAM.2016.7752329

Albanese, F., Feuerstein, E., & Balenzuela, P. (2024). *Polarization dynamics: a study of individuals shifting between political communities on social media.* Journal of Physics: Complexity, 5(3), 035008. DOI:10.1088/2632-072X/ad679d

Alnsour, Y., Alsharo, M., AL-Essa, M., & Smerat, A. (2025). *AI-Powered Election Insights: Predicting the 2024 Trump vs. Kamala Election Showdown with Machine Learning*. Journal of Intelligent Systems & Internet of Things, 15(1). DOI:10.54216/JISIoT.150116

Argandoña-Mamani, A., Ormeño-Alarcón, T., Iparraguirre-Villanueva, O., Paulino-Moreno, C., & Cabanillas-Carbonell, M. (2023). *Predicting Election Results with Machine Learning – A Review*. Proceedings of the International Congress on Information and Communication Technology. DOI:10.1007/978-981-99-3043-2_82

Atmojo, A. P. A., Arienaldi, N. A., Edbert, I. S., & Aulia, A. (2024). Sentiment Analysis of Quick Count Results of the 2024 *Indonesian Presidential Election on Social Media*. Proceedings of the 2024 11th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI). DOI: 10.1109/EECSI63442.2024.10776216

Barati, M. (2023). *Casual Social Media Use among the Youth: Effects on Online and Offline Political Participation*. JeDEM-EJournal of EDemocracy and Open Government, 15 (1), 1–21. DOI:10.29379/jedem.v15i1.738

Bermingham, A., O'Rourke, J., Gurrin, C., Collins, R., Irving, K., & Smeaton, A. F. (2013). *Automatically recommending multimedia content for use in group reminiscence therapy*. Proceedings of the 1st ACM international workshop on Multimedia indexing and information retrieval for healthcare, Barcelona, Spain. DOI: 10.1145/2505323.2505333

Boutet, A., Kim, H., & Yoneki, E. (2013). *What's on Twitter, I know what parties are popular and who you are supporting now!* Social network analysis and mining, 3(4), 1379-1391. DOI:10.1007/s13278-013-0120-1

Bovet, A., & Makse, H. A. (2019). *Influence of fake news on Twitter during the 2016 US presidential election.* Nature Communications, 10(1), 7. DOI:10.1038/s41467-018-07761-2

Brito, K., Silva Filho, R. L. C., & Adeodato, P. J. L. (2024). *Stop trying to predict elections only with Twitter – There are other data sources and technical issues to be improved*. Government Information Quarterly, 41(1), Paper no. 101899. DOI:10.1016/j.giq.2023.101899

Burnap, P., Avis, N. J., & Rana, O. F. (2013). *Making sense of self-reported socially significant data using computational methods.* International Journal of Social Research Methodology, 16(3), 215-230. DOI: 10.1080/13645579.2013.774174

Cedano, D., Picon, M. Y Ticona, W. (2024). *Sentiment Analysis Based on Twitter Comments Using Artificial Intelligence Techniques to Predict Peruvian Presidential Election Results*. Proceedings of the Computer Science Online Conference. DOI:10.1007/978-3-031-70518-2_17

Ceron, A., Curini, L., Iacus, S. M., & Porro, G. (2014). *Every tweet counts? How sentiment analysis of social media can improve our knowledge of citizens' political preferences with an application to Italy and France.* New media & society, 16(2), 340-358. DOI: 10.1177/1461444813480466

Chang, Y.-T., & Chuang, H.-M. (2024). *Applying deep learning for sentiment analysis: a case study of predicting the 2023 presidential election.* Proceedings of the IET International Conference on Engineering Technologies and Applications (ICETA 2024). DOI: 10.1049/icp.2024.4156

Demartini, G., Siersdorfer, S., Chelaru, S., & Nejdl, W. (2011). *Analyzing political trends in the blogosphere.* Proceedings of the International AAAI Conference on Web and Social Media. DOI: 10.1609/icwsm.v5i1.14178

Faria, F. T. J., Moin, M. B., Mumu, R. I., Abir, M. M. A., Alfy, A. N., & Alam, M. S. (2024). *Motamot: A Dataset for Revealing the Supremacy of Large Language Models over Transformer Models in Bengali Political Sentiment Analysis.* Proceedings of the 2024 IEEE Region 10 Symposium (TENSYMP). DOI: 0.1109/TENSYMP61132.2024.10752197

Firdaus, A. A., Yudhana, A., & Riadi, I. (2024). *Indonesian presidential election sentiment: Dataset of response public before 2024*. Data in Brief, 52, 109993. DOI: 10.1016/j.dib.2023.109993

Gaur, A., & Yadav, D. K. (2025). *A comprehensive analysis of forecasting elections using social media text.* Multimedia Tools and Applications, 1-33. DOI: 10.1007/s11042-024-20528-w

Gupta, R., Verma, H., & Kapoor, A. P. (2024). Neuromarketing in predicting voting behavior: A case of National elections in India. Journal of Consumer Behaviour, 23(2), 336-356. DOI: 10.1002/cb.2191

Gutiérrez, H., Zareei, M., de León Languré, A., & Brito, K. (2024*). Predicting the 2024 Mexican Presidential Election with Social Media*. Proceedings of the Mexican International Conference on Artificial Intelligence. DOI: 10.1007/978-3-031-75543-9_17

Gutierrez, H. A., De León, A., Zareei, M., & dos Santos, K. (2024). *Social Media for Predicting the Mexican Presidential Election: Beyond X and Facebook*. Proceedings of the 17th International Conference on Theory and Practice of Electronic Governance. DOI: 10.1145/3680127.368021

He, Y. S., Hassan, Wei, Zhongyu and Wong, Kam-Fai. (2012). *Quantising opinions for political tweets analysis*. Paper presented at the LREC 2012, Eighth International Conference on Language Resources and Evaluation, Istanbul, Turkey. URL: http://www.lrec-conf.org/lrec2012/

Hellwig, N. C., Fehle, J., Bink, M., Schmidt, T., & Wolff, C. (2024). *Exploring Twitter discourse with BERTopic: topic modeling of tweets related to the major German parties during the 2021 German federal election*. International Journal of Speech Technology, 27(4), 901-921. DOI:10.1007/s10772-024-10142-4

Kenosi, C., Zlotnikova, I., & Sigwele, T. (2024). *Industrial Revolution 4.0 technologies for democratic e-government services: A systematic review of transformational frameworks*. JeDEM-eJournal of eDemocracy and Open Government, 16(3). DOI: 0.29379/jedem.v16i3.921

Kumari, S., & Singh, M. P. (2024). *Machine Learning-Based Election Results Prediction Using Twitter Activity*. SN Computer Science, 5(7), 819. DOI: 10.1007/s42979-024-03180-x

Liu, R., Yao, X., Guo, C., & Wei, X. (2021). *Can we forecast the presidential election using Twitter data? An integrative modelling approach.* Annals of GIS, 27(1), 43-56. DOI: 10.1080/19475683.2020.1829704

Ma'Aly, A. N., Pramesti, D., & Fakhrurroja, H. (2024). *Comparative Analysis of Deep Learning Models for Multi-label Sentiment Classification of 2024 Presidential Election Comments*. Paper presented at the 2024 7th International Conference on Informatics and Computational Sciences (ICICoS). DOI: 10.1109/ICICoS62600.2024.10636889.

Ma'aly, A. N., Pramesti, D., Fathurahman, A. D., & Fakhrurroja, H. (2024). *Exploring Sentiment Analysis for the Indonesian Presidential Election Through Online Reviews Using Multi-Label Classification with a Deep Learning Algorithm.* Information, 15(11), 705. DOI: 10.3390/info15110705

Matloga, P., Marivate, V., & Olaleye, K. (2025). Sentiment analysis using unsupervised learning for local government elections in South Africa. JeDEM-eJournal of eDemocracy and Open Government, 17(1), 144-169. DOI: 10.29379/jedem.v17i1.945

Metaxas, P. T., Mustafaraj, E., & Gayo-Avello, D. (2011). *How (Not) to Predict Elections*. Paper presented at the 2011 IEEE Third Int'l Conference on Privacy, Security, Risk and Trust (PASSAT) / 2011 IEEE Third Int'l Conference on Social Computing (SocialCom). DOI:10.1109/PASSAT/SocialCom.2011.98

Mishra, P., Punia, D., Sikka, G., Sharma, A. K., & Sikka, K. (2024). *Evaluating Various Techniques for Twitter Sentiment Analysis for Election Results.* Paper presented at the 2024 First International Conference on Pioneering Developments in Computer Science & Digital Technologies (IC2SDT). DOI:10.1109/IC2SDT62152.2024.10696204

Mohammad, S. M., Dorr, B. J., Hirst, G., & Turney, P. D. (2013). *Computing lexical contrast*. Computational Linguistics, 39(3), 555-590. DOI:10.1162/COLI_a_00143

Monti, C., Rozza, A., Zappella, G., Zignani, M., Arvidsson, A., & Colleoni, E. (2013). *Modelling political disaffection from Twitter data.* Paper presented at the Proceedings of the Second International Workshop on Issues of Sentiment Discovery and Opinion Mining, Chicago, Illinois. DOI:10.1145/2502069.2502072

Mustafaraj, E., & Metaxas, P. T. (2011). *What edited retweets reveal about online political discourse*. Proceedings of the 5th AAAI Conference on Analyzing Microtext.

Nakov, P., Rosenthal, S., Kiritchenko, S., Mohammad, S. M., Kozareva, Z., Ritter, A., . . . Zhu, X. (2016). *Developing a successful SemEval task in sentiment analysis of Twitter and other social media texts.* Language Resources and Evaluation, 50(1), 35-65. DOI:10.1007/s10579-015-9328-1

Odegbile, A. T., & Oyelami, O. M. (2024). *A dataset of the 2023 presidential election in Nigeria*. Data in Brief, 57, 110847. DOI: 10.1016/j.dib.2024.110847

Oikonomou, L., & Tjortjis, C. (2018, 22-24 Sept. 2018). *A Method for Predicting the Winner of the USA Presidential Elections using Data extracted from Twitter.* Paper presented at the 2018 South-Eastern European Design Automation, Computer Engineering, Computer Networks and Society Media Conference (SEEDA_CECNSM). DOI:10.23919/SEEDA-CECNSM.2018.8544919

Purwandari, K., Jiwanggi, M. A., & Yulianti, E. (2024). *Sentiment Analysis on YouTube Comment Data for the Candidate Debate in the 2024 Presidential Election of the Republic of Indonesia*. Paper presented at the 2024 5th International Conference on Artificial Intelligence and Data Sciences (AiDAS). DOI:10.1109/AiDAS63860.2024.10730443

Qorib, M., Gizaw, R. S., & Kim, J. (2023). *Impact of Sentiment Analysis for the 2020 US Presidential Election on Social Media Data.* Proceedings of the 2023 8th International Conference on Machine Learning Technologies. DOI: 10.1145/3589883.3589888

Rahman, A. B. A., & Suarga, H. (2024). *Exploring the impact of social media on political discourse: a case study of the Makassar mayoral election.* International Journal of Advanced Technology and Engineering Exploration, 11(114), 708. DOI: 10.19101/IJATEE.2023.10102458

Razzaq, M. A., Qamar, A. M., & Bilal, H. S. M. (2014). *Prediction and analysis of the Pakistan election 2013 based on sentiment analysis.* Proceedings of the 2014 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, Beijing, China. DOI: 10.1109/ASONAM.2014.6921662

Reiki, M. K. A., & Sibaroni, Y. (2024). *Improving Feature Extraction for Sentiment Analysis on Indonesian Election 2024 Using Term Weighting with FastText.* Paper presented at the 2024 International Conference on Data Science and Its Applications (ICoDSA). DOI: 10.1109/ICoDSA62899.2024.10652172

Robertson, S. P. (2011, 4-7 January). *Changes in Referents and Emotions over Time in Election-Related Social Networking Dialog.* Paper presented at the Proceedings of the 44th Hawaii International Conference on System Sciences (HICSS-44), Kauai, Hawaii, USA. DOI: 10.1109/HICSS.2011.97

Roskoshnyi, I. (2024). *Direct democracy and AI as a way to revitalize the health of the Federal Commonwealth.* JeDEM-eJournal of eDemocracy and Open Government, 16(1), 1-27. DOI:10.29379/jedem.v16i1.872

Samosir, F. V. P., & Riyaldi, S. (2024). *Sentiment Analysis of TikTok Comments on Indonesian Presidential Elections Using IndoBERT*. Paper presented at the 2024 3rd International Conference on Creative Communication and Innovative Technology (ICCIT). DOI: 10.1109/ICCIT62134.2024.10701256

Santana, J., Santana, M., Sampaio, P., & Brito, K. (2024). *Towards a Methodology for Analyzing Visual Elements in Social Media Posts of Politicians.* Proceedings of the 17th International Conference on Theory and Practice of Electronic Governance. DOI: 10.1145/3680127.3680218

Singhal, K., Sood, K., Kaushal, A., Gehlot, V., & Rana, P. S. (2023). *Analysis of the Effectiveness of Indian Political Campaigns on Twitter*. Proceedings of the International Advanced Computing Conference. DOI:10.1007/978-3-031-56700-1_17

Srinivasan, S. M., & Paat, Y.-F. (2024). *A Data-Centric Approach to Understanding the 2020 US Presidential Election.* Big Data and Cognitive Computing, 8(9), 111. DOI:10.3390/bdcc8090111

Stieglitz, S., & Dang-Xuan, L. (2013). *Emotions and information diffusion in social media – sentiment of microblogs and sharing behavior.* Journal of Management Information Systems, 29(4), 217-248. DOI:10.2753/MIS0742-1222290408

Sutrisno, D., Martina, M., Karsana, D., Annury, M. N., Adri, A., Damayanti, W., . . . Juliastuty, D. (2024). *Semiotic Analysis of Psycholinguistic Strategies in Indonesian President Candidates' Debates 2024: Unraveling Linguistic Signifiers and Mental Processes in Argumentative Discourse*. Proceedings of the Forum for Linguistic Studies. DOI:/10.30564/fls.v6i5.7251

Tanaja, R. N., Widjaya, A., Gunawan, A. A. S., & Setiawan, K. E. (2024). *Evaluating Public Opinion on the 2024 Indonesian Presidential Election Candidate: An IndoBERT Approach to Twitter Sentiment Analysis.* Proceedings of the 2024 10th International Conference on Smart Computing and Communication (ICSCC). DOI: 10.1109/ICSCC62041.2024.10690796

Trachanas, G., Valavani, C., Alexandris, C., & Giannakis, S. (2024). *Vocal Minority Versus Silent Majority: Twitter Data for Greek General Elections and Tweets on German Foreign Policy*. Proceedings of the International Conference on Human-Computer Interaction. DOI: 10.1007/978-3-031-60405-8_25

Tripathi, M., Moorthy, C., & Nemade, V. (2024). *Mathematical modelling and implementation of NLP for the prediction of election results based on social media Twitter engagement and polls*. International Journal of Intelligent Systems and Applications in Engineering, 12(14s), 184-191.

Tripathi, M. K., & Neelakantappa, M. (2024). *Election Results Prediction Using Twitter Data by Applying NLP.* International Journal of Intelligent Systems and Applications in Engineering, 12(11s), 537 - 546. Retrieved February 2, 2025, from https://ijisae.org/index.php/IJISAE/article/view/4474

Tumasjan, A., Sprenger, T., Sandner, P., & Welpe, I. (2010). *Predicting elections with Twitter: What 140 characters reveal about political sentiment*. Proceedings of the international AAAI conference on web and social media. DOI: 10.1609/icwsm.v4i1.14009

Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. (2012). *Where there is a sea, there are pirates: Response to Jungherr, Jürgens, and Schoen.* Social Science Computer Review, 30(2), 235-239. DOI: 10.1177/0894439311404123

Turney, S. M. M. a. P. D. (2013). Nrc emotion lexicon. National Research Council, Canada, 2, 234. National Research Council, Canada, 2, 234.

Unankard, S., Li, X., Sharaf, M., Zhong, J., & Li, X. (2014, 2014//). *Predicting Elections from Social Networks Based on Sub-event Detection and Sentiment Analysis.* Proceedings of the Web Information Systems Engineering – WISE 2014, Cham.DOI: 10.1007/978-3-319-11746-1_1

Upreti, A., Pokhrel, L., Ban, H., & Gurung, K. (2025). *Decoding Digital Campaigns: A Multi-method Analysis of Facebook Posts during 2022 Parliamentary Elections in Nepal.* Asia Pacific Journal of Information Systems, 35(1), 195-215. DOI: 10.14329/apjis.2025.35.1.195

Valle-Cruz, D., Sandoval-Almazán, R., López-Chau, A., & Criado, J. I. (2024). *Unveiling political polarization on Twitter: Machine learning and sentiment analysis in presidential elections*. JeDEM-eJournal of eDemocracy and Open Government, 16(1), 186-212. DOI: 10.29379/jedem.v16i1.846

Wang, J., Sundar, S. S., & Ram, N. (2024). *Can Social Media Engagement Predict Election Results? Bandwagon Effects of Tweets About US Senate Candidates*. Social Media+ Society, 10(4), 20563051241298449.DOI: 10.1177/2056305124129844

Wong, F. M. F., Tan, C. W., Sen, S., & Chiang, M. (2016). *Quantifying Political Leaning from Tweets, Retweets, and Retweeters*. IEEE Transactions on Knowledge and Data Engineering, 28(8), 2158-2172. DOI:10.1109/TKDE.2016.2553667. DOI: 10.1109/TKDE.2016.2553667

Yaqub, U., Chun, S. A., Atluri, V., & Vaidya, J. (2017, June 7-9). *Sentiment-Based Analysis of Tweets During the US Presidential Elections.* Proceedings of the 18th Annual International Conference on Digital Government Research (dg.o 2017), New York, NY. DOI: 10.1145/3085228.308528

Yates, D., Mentzer, K., & Tousignant, C. (2024). *An Analysis of Partisan Polarization in the 2022 US Senate Races*. https://aisel.aisnet.org/amcis2024/soc_inclusion/social_inclusion/16

About the Author

Kapil Gurung

Kapil Gurung, Ph.D., is an Assistant Professor of Marketing at Seoul Christian University, South Korea. He earned his doctorate in Business Administration from Ajou University in consumer behavior, digital marketing, and e-commerce. His research focuses on sentiment analysis, digital marketing, and consumer behavior, with publications on social media campaigning, election sentiment, and tourism marketing. He has over three years of teaching experience in business and marketing, and he actively mentors graduate and undergraduate students while contributing to interdisciplinary research in marketing and information systems.

Appendix A

Main themes and key insights of studies on sentiment analysis during the election

Themes	Key Insights and Relevant Information
Social Media Engagement as a Proxy for Voter Sentiment (11)	Early study claiming X mentions reflect German election results (Tumasjan et al., 2010). Infers voter support from X engagement for the UK election. (Boutet et al., 2013). Models voter disaffection via X engagement in Italian elections (Monti et al., 2013). Uses engagement sub-events to reflect the voter.(Unankard et al., 2014). Maps 2016 U.S. election trends through X engagement.(Bovet & Makse, 2019). Links tweet cascades to U.S. Senate race voter sentiment (Wang et al., 2024). Uses YouTube comments as a proxy for Indonesian election sentiment (Purwandari et al., 2024). Examines TikTok comments as voter sentiment indicators (Samosir & Riyaldi, 2024). Multi-platform engagement, such as Instagram and YouTube, is a voter sentiment proxy for Mexico (Gutierrez et al., 2024). X engagement dataset reflecting pre-election sentiment (Firdaus, Yudhana, & Riadi, 2024). Reddit posts as a proxy for U.S. election sentiment (Alnsour et al., 2025).

Dynamics in Sentiment Analysis (9)	Examines Facebook's reaction-based sentiment dynamics (Robertson, 2011). Analyzes X's microblogging influence on sentiment. (Stieglitz & Dang-Xuan, 2013). Highlights X's real-time dynamics for Irish election sentiment (Bermingham et al., 2013). Focuses on Facebook's reaction-specific sentiment for the U.S. election. (Alashri et al., 2016). Develops visual sentiment analysis for Instagram's unique format. (Santana et al., 2024). Uses X's discourse structure for sentiment and topic modeling (Hellwig et al., 2024). Critiques X's limitations, advocating multi-platform dynamics (Brito et al., 2024). Compares YouTube's multi-label sentiment dynamics with deep learning (Ma'Aly, Pramesti, & Fakhrurroja, 2024; Ma'aly, Pramesti, Fathurahman, et al., 2024). Highlights Reddit's unique value for studying political discourse into public reasoning and narrative framing (Alnsour et al., 2025).
Advancements (10)	Early sentiment quantification method for X (He, 2012). Introduces semantic sentiment analysis and creates a motion lexicon for political tweet sentiment (Turney, 2013). Design sentiment analysis benchmarks for X (Nakov et al., 2016). Integrates sentiment models for X election forecasting (Liu et al., 2021). Compares VADER and BERT for X sentiment accuracy (Mishra et al., 2024). Enhances feature extraction for X sentiment analysis (Reiki & Sibaroni, 2024). Test LLMs (Gemini 1.5 Pro) for Bengali tweet sentiment accuracy (Faria et al., 2024) Uses IndoBERT for advanced X sentiment analysis (Tanaja et al., 2024). Employs deep learning for sentiment analysis in elections (Chang & Chuang, 2024). Develops a machine learning-based sentiment tool for Nigerian tweets (Agagu & Gbadebo, 2024).

Methodological and Ethical Considerations (11)	Critiques methodological flaws in X-based predictions. (Metaxas et al., 2011). Examines ambiguity in retweet sentiment and discourse.(Mustafaraj & Metaxas, 2011). Raises methodological issues in blog sentiment analysis.(Demartini, 2011). Defends methodology against critique, addressing challenges (Tumasjan, Sprenger, Sandner, & Welpe, 2012). Discusses methodological limits in X sentiment for preferences (Ceron et al., 2014). Evaluates methodological accuracy and ethical implications for the 2020 U.S. election. (Qorib et al., 2023). Notes sarcasm and noise as methodological challenges in Peruvian tweets (Cedano et al., 2024). Addresses ethical data collection challenges with the Nigerian tweet dataset (Odegbile & Oyelami, 2024). Raises ethical concerns about neuromarketing and sentiment manipulation (Gupta et al., 2024). Reviews methodological advancements and challenges in prediction accuracy (Argandoña-Mamani et al., 2023). Highlights noise and bias as persistent methodological issues (Gaur & Yadav, 2025).
Polarization and Echo Chambers (8)	Quantifies partisan skew and polarization on Twitter in U.S. elections (Wong et al., 2016). Notes polarization's impact on X prediction accuracy. (Oikonomou & Tjortjis, 2018). Analyzes X's role in amplifying partisan, polarized sentiment in U.S. Senate races (Yates et al., 2024). Tracks polarization shifts in U.S. election X communities (Albanese et al., 2024). Examines vocal minority vs. silent majority dynamics in Greek elections (Trachanas et al., 2024). Highlights echo chambers skewing U.S. election sentiment on X (Srinivasan & Paat, 2024). Notes polarization in quick count sentiment models for Indonesia (Atmojo et al., 2024). Assess X's role in amplifying partisan polarization during presidential elections (Valle-Cruz et al., 2024).

Political Campaigns and Digital Governance (8)	Shows the use of sentiment in Pakistan campaign strategies. (Razzaq et al., 2014). Analyzes the sentiment's role in shaping Indonesian campaign strategies (Sutrisno et al., 2024). Demonstrates Twitter sentiment guiding Indian campaign tactics (Kumari & Singh, 2024). Examines X's influence on local election discourse and governance (Rahman & Suarga, 2024). Assesses X sentiment's impact on Indian campaign effectiveness (Singhal et al., 2023). Offers NLP-based tools for campaign and governance insights. (Tripathi et al., 2024). Reviews sentiment's broader implications for campaigns and governance (Gaur & Yadav, 2025). Investigate Social media's role in youth political participation for inclusive campaign and governance strategies (Barati, 2023).

