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Implementation of Toxicity, Sentiment, and Social Network Analysis (Epic Rap Battles of Presidency 2024)

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Abstract−This research delves into the complex realm of digital political communication, employing a comprehensive approach that integrates toxicity analysis, sentiment classification, and social network analysis within the framework of the CRISP-DM methodology. The study illuminates the multifaceted nature of online discourse through meticulous examination, elucidating the coexistence of harmful content, diverse sentiments, and intricate network structures. Leveraging VADER and TextBlob algorithms, toxicity and sentiment distribution patterns are meticulously identified, with metrics such as Toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat presenting distinct numerical values. For instance, Toxicity measures at 0.09275 with a severe threshold of 0.98622, while sentiment analysis reveals varying proportions of negative, neutral, and positive sentiments across English, French, and German content. Specifically, VADER sentiment analysis for English content shows 25.38% classified as unfavorable, 41.13% as neutral, and 33.49% as positive sentiments, while TextBlob sentiment analysis for English content displays 8.59% negative, 64.12% neutral, and 27.29% positive sentiments. Similarly, TextBlob sentiment analysis for French content indicates 1.75% negative, 96.49% neutral, and 1.75% positive sentiments, and for German content, it illustrates 2.00% negative, 96.52% neutral, and 1.48% positive sentiments. These findings provide crucial insights into public sentiment, information dissemination, and community formation within online political discourse. The implications of this research extend to policymakers, electoral candidates, and digital platform developers, offering evidence-based strategies to cultivate healthier online environments and promote informed civic engagement. Further investigation is warranted to explore emerging trends and adapt analytical frameworks to the evolving landscape of digital communication. Ultimately, this study advances our understanding of digital political communication and underscores the necessity of interdisciplinary approaches in addressing contemporary socio-political challenges in the digital era.

Keywords: Political; Discourse; Communication; Engagement; Voting; Behavior

1. INTRODUCTION

In the contemporary digital landscape, the proliferation of political content across social media and similar platforms has captivated users, fostering engagement and discourse on pertinent political issues. This surge in digital content dissemination signifies a transformative shift in the dissemination and consumption of political discourse [1]–[3]. As users navigate myriad political narratives and perspectives, they are compelled to participate actively in discussions, shaping public opinion and influencing political discourse [4]–[6]. Consequently, the digital realm has emerged as a pivotal arena for political engagement and awareness, transcending traditional boundaries and democratizing access to information [7], [8]. This dynamic interaction between users and digital content underscores the profound impact of technology on modern political discourse, underscoring the necessity for critical analysis and discernment amidst the digital deluge.

The influence of political content on social media significantly shapes perceptions and actions regarding the selection of candidates. As users are exposed to diverse political narratives and ideologies disseminated through social platforms, their perceptions of candidates are often shaped by the content they encounter [9]–[12]. Furthermore, the interactive nature of social media facilitates the spread of positive and negative information, influencing users' opinions and attitudes towards specific candidates [13], [14]. Consequently, individuals may be inclined to support or oppose a candidate based on the content they encounter, ultimately impacting their voting behavior [15], [16]. This underscores the transformative role of social media in modern political campaigns, where digital discourse has become instrumental in shaping electoral outcomes and political landscapes.

Political content is creatively packaged in digital works like parody music videos. These multimedia productions serve as potent vehicles for conveying political messages in an engaging and accessible manner, leveraging the power of music, humor, and visual storytelling to captivate audiences [17]. Through parody music videos, complex political issues are simplified and disseminated to a broader audience, fostering greater awareness and understanding [18], [19]. Furthermore, these productions often incorporate satirical elements to critique political figures or policies, prompting viewers to reflect on societal norms and power dynamics [20]. As such, parody music videos represent a dynamic intersection of entertainment and political commentary, exemplifying the evolving landscape of digital activism and expression.

This research uses the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology to analyze the toxicity, sentiment, and social network dynamics of epic rap battle content within the context of the presidential election. By employing this structured approach, the study seeks to systematically examine the linguistic toxicity levels, sentiment patterns, and network interactions inherent within epic rap battle content related to presidential elections. This research provides a comprehensive understanding of the multifaceted nature of these digital

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interactions, thereby shedding light on their potential impacts on political discourse and public opinion formation [21]–[23]. Ultimately, this research aims to contribute valuable insights into the evolving landscape of political communication and digital engagement within contemporary elections.

The urgency of this research lies in its potential to offer invaluable insights into the rapidly evolving landscape of digital political discourse, particularly within the context of presidential elections. By systematically analyzing the toxicity, sentiment, and social network dynamics of epic rap battle content through the CRISP-DM methodology, this study aims to address critical gaps in our understanding of the impact of such unconventional political communication channels [24]–[26]. With the proliferation of digital platforms and the increasing influence of online content on public opinion and political behavior, there is a pressing need to elucidate the mechanisms through which these mediums shape electoral outcomes and democratic processes [27]–[29]. Therefore, this research contributes to academic scholarship and holds practical significance for policymakers, political strategists, and civil society stakeholders striving to navigate and harness the power of digital media in contemporary political contexts.

This research's theoretical and practical contributions are substantial in advancing our understanding of digital political communication and its real-world implications. This study offers theoretical insights into the intersection of technology, politics, and society by applying the CRISP-DM methodology to analyze toxicity, sentiment, and social network dynamics within epic rap battle content during presidential elections. By uncovering patterns and trends in online discourse, scholars can refine existing theories and frameworks related to digital activism, political participation, and public opinion formation [30]–[33]. Moreover, the practical implications of this research are far-reaching, as it provides actionable insights for policymakers, electoral candidates, and digital platforms to navigate the ethical, legal, and social implications of online political engagement [34], [35]. This research contributes to academic discourse by bridging theory and practice and informs evidence-based strategies for fostering healthy and inclusive digital political environments.

In similar research, this study complements existing literature by offering a novel approach to analyzing digital political communication through the lens of epic rap battles within presidential elections. While prior research has explored various forms of online political discourse, such as social media interactions and political advertising, examining epic rap battles represents a unique and understudied aspect of digital activism and expression [36]–[41]. By employing the CRISP-DM methodology to investigate toxicity, sentiment, and social network dynamics within this context, this research expands the knowledge of digital political communication, shedding light on the efficacy and impact of unconventional political engagement [42]–[44]. Through its innovative methodology and focus on a distinct genre of digital content, this study contributes valuable insights to scholars, practitioners, and policymakers seeking to understand and navigate the complexities of contemporary political communication in the digital age.

The limitation of this research pertains to the scope of data analysis, where the dataset may not fully represent the entirety of digital political communication dynamics. While this study offers valuable insights into toxicity analysis, sentiment classification, and social network analysis, the findings may be subject to biases in the data collection. Additionally, the reliance on specific algorithms such as VADER and TextBlob for sentiment analysis introduces limitations related to the accuracy and cultural context of sentiment classification. Despite these constraints, our research is a foundational exploration into the complexities of digital political communication, providing a framework for future studies to expand upon and refine methodologies for a more comprehensive understanding of online discourse.

2. RESEARCH METHODOLOGY

2.1 Gap Analysis of Political Content, Communication, Participation, and Voting Behavior

The gap analysis of political content, digital communication, and voting behavior reveals a critical disparity between traditional theoretical frameworks and the rapidly evolving landscape of digital political engagement. While existing literature provides valuable insights into the influence of mass media and interpersonal communication on voting behavior, there is a noticeable dearth of understanding of the nuanced dynamics of digital platforms and their impact on electoral outcomes [45], [46]. This discrepancy underscores the need for comprehensive research that bridges the gap between traditional and digital communication channels, integrating advanced methodologies to analyze the multifaceted dimensions of online political discourse [47], [48]. By addressing this gap, scholars can better understand how digital content consumption, social network interactions, and algorithmic processes shape voter perceptions and decisions, ultimately informing evidence-based strategies for political campaigns and democratic governance in the digital era.

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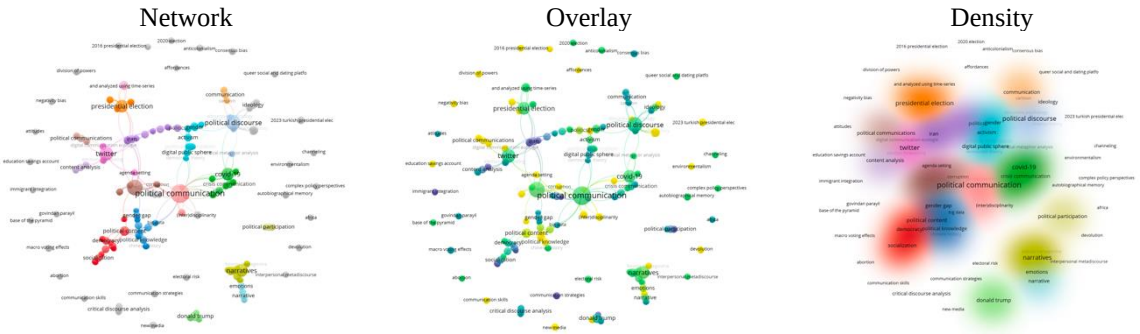

Figure 1. Network, Overlay, and Density (VosViewer)

Figure 1 shows the network, overlay, and density of the gap analysis process using VosViewer. Based on the findings of the gap identification, it is evident that there is an interconnected relationship among political communication, political content, political participation, presidential election, and voting behavior. This interrelationship underscores the intricate web of influences shaping modern democratic processes, where digital platforms serve as pivotal conduits for disseminating political content, fostering political engagement, and ultimately impacting voting behavior [49]–[51]. As individuals navigate through a barrage of digital content and engage in online political discourse, their perceptions and behaviors are shaped by a complex interplay of factors, including the nature of political communication, the quality and tone of political content, and the dynamics of political participation [52], [53]. Consequently, understanding these interconnected topics is essential for developing comprehensive strategies to enhance democratic governance and mitigate the risks associated with digital misinformation and manipulation in electoral processes.

2.2 Cross-Industry Standard Process for Data Mining (CRISP-DM)

This research employs the CRISP-DM methodology to implement toxicity analysis, sentiment classification, and social network analysis, reflecting a systematic and comprehensive approach to studying digital political communication. By leveraging the CRISP-DM framework, which encompasses six distinct phases—business understanding, data understanding, data preparation, modeling, evaluation, and deployment—this study ensures rigor and reliability in its analytical processes. The toxicity analysis identifies and mitigates harmful or offensive content within political discourse. At the same time, sentiment classification allows for categorizing opinions and attitudes expressed in digital content. Furthermore, social network analysis facilitates the exploration of interconnected relationships and information flow among users, shedding light on the diffusion of political narratives and the formation of online communities. By integrating these methodological approaches, this research aims to provide nuanced insights into the complexities of digital political communication, contributing to a deeper understanding of its impact on societal discourse and democratic processes.

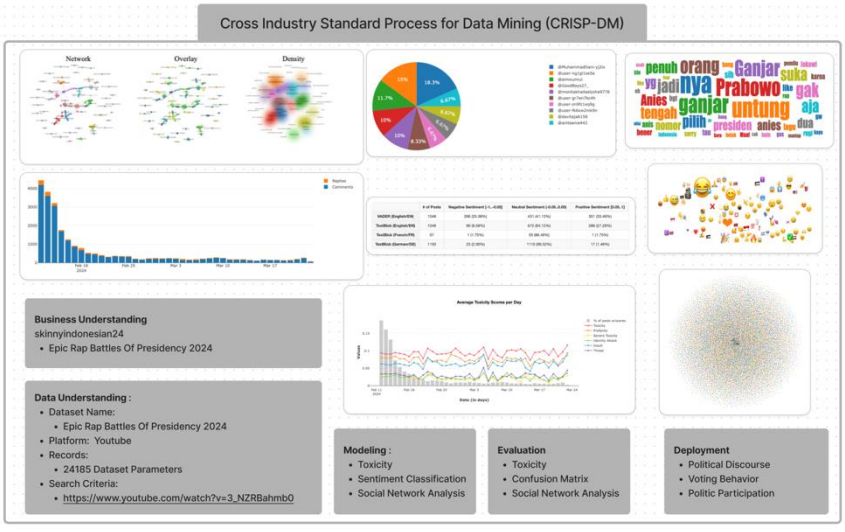

Figure 2. CRISP-DM Framework

Figure 2 shows the CRISP-DM framework of this research. The superiority of the CRISP-DM methodology lies in its structured and iterative approach to data mining projects, which ensures efficiency, reliability, and reproducibility in analysis. As a widely recognized industry standard, CRISP-DM offers a systematic framework encompassing distinct phases of business understanding, data understanding, data preparation, modeling, evaluation, and deployment that guide researchers through the entire data mining process. This structured approach facilitates

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clear delineation of project goals, thorough exploration of available data sources, and rigorous validation of analytical models, thereby enhancing the robustness and credibility of research outcomes. Moreover, CRISP-DM's iterative nature allows for continuous refinement and improvement of analytical techniques, enabling researchers to adapt to evolving data landscapes and address emerging research questions effectively. In conclusion, the comprehensive and flexible nature of CRISP-DM empowers researchers to navigate complex data mining projects with confidence, ultimately yielding valuable insights and advancing knowledge in diverse domains.

2.2.1 Business Understanding

During the business understanding phase, the discussion focuses on the political context surrounding the presidential election and political issues encapsulated within the music video with ID 3_NZRBahmb0 titled "Epic Rap Battles Of Presidency 2024." This phase is the foundation for subsequent data mining processes, emphasizing the importance of understanding the objectives, stakeholders, and relevant domain knowledge. By delving into the political landscape depicted in the music video, researchers gain insights into the themes, narratives, and societal discourse surrounding the presidential election of 2024. This preliminary analysis lays the groundwork for subsequent phases of the CRISP-DM methodology, guiding researchers in effectively harnessing data and extracting meaningful insights about digital political communication and voter behavior.

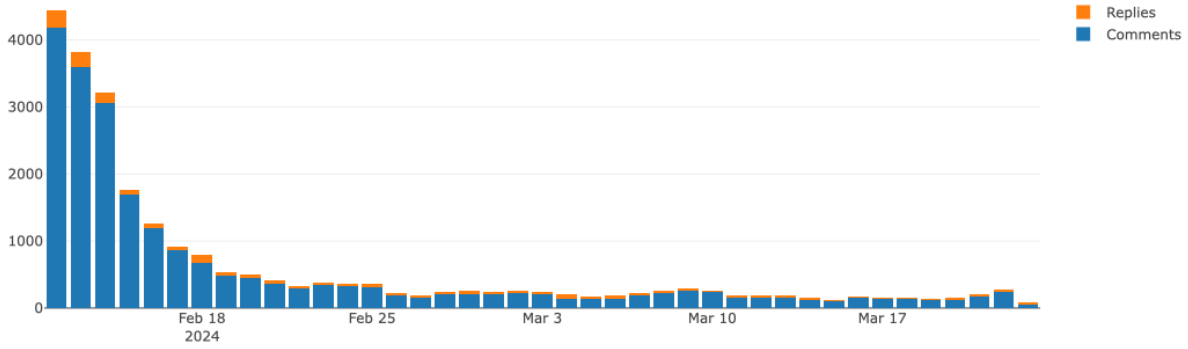

Figure 3. Post-per-day Statistic of the Video (Communalytic)

Figure 3 shows the post-per-day statistics of the music video. Based on statistical data on post-per-day from the video content, it is evident that on February 12, 2024, there were 4184 posts with 249 engagements, 3609 posts, and 194 engagements on February 13, and 3070 posts with 140 engagements on February 14. These figures illustrate fluctuations in user activity over the specified period, potentially reflecting shifts in audience engagement and interest levels. Such statistical insights are instrumental in understanding user behavior patterns and interaction with digital content, providing valuable context for further analysis within digital political communication. By leveraging quantitative data metrics, this research discerns trends and dynamics within online discourse, facilitating a deeper understanding of the impact of digital platforms on political engagement and public opinion formation.

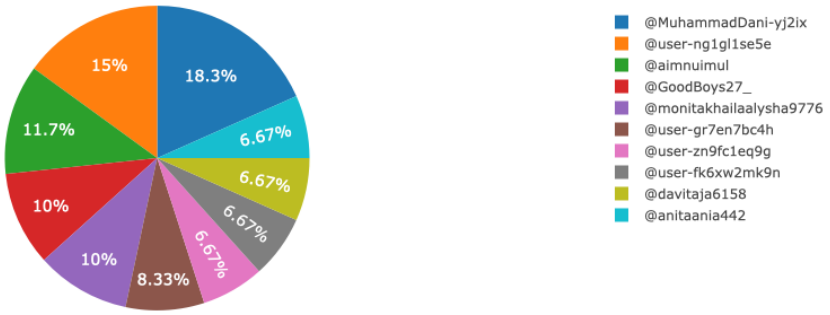

Figure 4. Top Ten Poster (Communalytic)

Figure 4 shows the top ten posters. Based on statistical data regarding the top ten posters, it is discernible that @MuhammadDani-yj2ix has the highest number of posts, totaling 11, followed by @user-ng1gl1se5e with nine posts, and @aimnuimul with seven posts. These statistics highlight the prominence of specific users in contributing content to the platform, indicating their influence within the online community. Such insights into user activity and engagement patterns are instrumental in understanding digital discourse dynamics and political content dissemination. By analyzing the contributions of top posters, this research identifies key influencers and trends within digital political communication, informing strategies for engaging with online audiences and shaping public opinion effectively.

2.2.2 Data Understanding

Based on the results of identifying statistical data on post-per-day and the top ten posters, discernible data characteristics to be processed in the modeling phase emerge. These characteristics encompass variations in daily

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posting frequency, as evidenced by fluctuations in post-per-day statistics, indicating dynamic user engagement patterns over time. Additionally, the prominence of specific users among the top ten posters highlights the presence of influential individuals within the online community, potentially influencing the dissemination and reception of political content. Such insights into the characteristics of the data underscore the complexity and richness of digital discourse surrounding the analyzed content, providing researchers with valuable context for developing and refining analytical models in subsequent phases. Thus, leveraging these identified data characteristics is essential for constructing robust models that accurately capture the dynamics of digital political communication and inform evidence-based insights into user behavior and engagement patterns.

Figure 5. Frequently Used Words (Communalytic)

Figure 5 shows the frequently used words. Identifying frequently used words reveals key linguistic patterns within the analyzed content. Notably, words such as "nya" appear 55 times, followed closely by "untung" with 51 occurrences and "ganjar" with 47 mentions. These recurrent themes suggest their significance in discussions surrounding the analyzed topic. Additionally, political figures like "Prabowo" are mentioned 46 times, "Ganjar" 42 times, and "Anies" 28 times, highlighting the salience of political discourse within the dataset. The prevalence of "presiden" occurring 25 times and "pilih" with 31 mentions further indicates a focus on political leadership and electoral decision-making. Such insights into frequently used words provide researchers valuable context for understanding the prevailing themes and sentiments within the analyzed content, facilitating more profound insights into public discourse and opinion formation processes.

Figure 6. Emoji Cloud (Communalytic)

Figure 6 shows the emoji clouds of the first and second music videos. Identifying emoji clouds reveals specific numerical patterns in emotive expressions within the analyzed content. Notably, the "😂" emoji appears 98 times, indicating a prevalent use of humorous or light-hearted sentiment among users. Following closely, "❤️" and "😊" appear 50 and 49 times, respectively, suggesting a substantial presence of affectionate and cheerful expressions. Conversely, "😢" and "😭" are used 19 and 13 times, respectively, hinting at somber or emotive content. These numerical observations underscore the diverse emotions conveyed through emojis, providing quantitative insights into the digital discourse's emotional tone and thematic composition. Such numerical analyses contribute to a more comprehensive understanding of user engagement and sentiment within digital political communication.

Upon comprehending the characteristics of the data, the modeling process can be initiated to conduct toxicity analysis, sentiment classification, and social network analysis. This research constructs robust models that capture the nuances of digital political communication by leveraging the insights gained from identifying statistical patterns, such as post-per-day frequencies and the prevalence of specific emojis. These models facilitate the systematic examination of toxicity levels, sentiment polarities, and network structures within the analyzed content, providing valuable insights into the quality of online discourse and the dynamics of user interactions. Through modeling, this research uncovers underlying patterns, relationships, and trends that inform a deeper understanding of digital political communication, thereby contributing to advancing knowledge in the field.

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2.2.3 Modeling

The modeling process is divided into three main components: toxicity analysis, Vader and TextBlob sentiment classification, and social network analysis. Each component is crucial in elucidating different aspects of digital political communication. Toxicity analysis aims to assess the level of toxicity or harmfulness in the content, providing insights into the quality of online discourse and potential risks associated with certain narratives. Vader and TextBlob, sentiment classification techniques, enable categorizing text-based content into positive, negative, or neutral sentiments, offering valuable insights into the emotional tone and attitudes expressed within the digital discourse. Additionally, social network analysis allows researchers to examine the structure and dynamics of user interactions, uncovering influence patterns and information dissemination within online communities. By integrating these three components into the modeling process, researchers can develop comprehensive analyses illuminating various dimensions of digital political communication, contributing to a deeper understanding of its impact on society and democratic processes.

2.2.4 Evaluation

During the evaluation phase, toxicity is assessed based on various dimensions, including Toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat. This comprehensive evaluation framework allows researchers to systematically analyze the harmfulness and appropriateness of digital content within political communication. By considering multiple facets of toxicity, this research gains a nuanced understanding of the potential risks associated with online discourse, informing evidence-based strategies for mitigating harmful content and fostering healthier digital environments. The evaluation phase is critical in assessing the effectiveness and ethical implications of digital political communication analyses, ultimately contributing to the responsible use of technology in democratic processes.

The results of implementing Vader and TextBlob sentiment classification are visualized through the distribution of polarity values. This visualization clearly and concisely represents the emotional tone and sentiment of the analyzed content. By plotting the distribution of polarity scores, this research identifies trends, patterns, and outliers in sentiment across different segments of the digital discourse. Such visualizations enhance the interpretability of sentiment analysis results, facilitating more profound insights into the attitudes and perceptions conveyed within the text. Through the visualization of polarity distributions, this research effectively communicates findings. It draws meaningful conclusions regarding the emotional dynamics of digital political communication, contributing to a more comprehensive understanding of public sentiment and opinion formation in online environments.

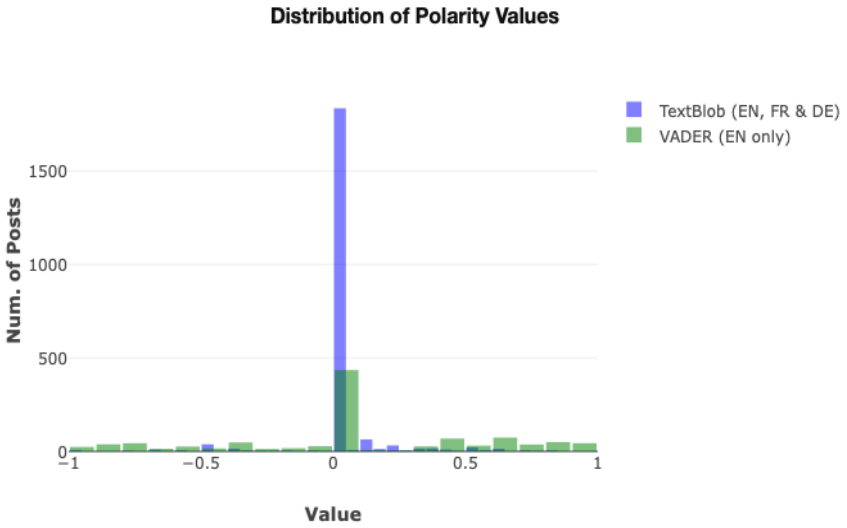

Figure 7. Distribution of Polarity Values

Figure 7 shows the distribution of polarity values. Based on the distribution of polarity values, it is evident that both VADER and TextBlob sentiment classification algorithms exhibit distinct patterns in sentiment analysis. Specifically, in the case of VADER, 25.38% of the analyzed content is classified as unfavorable, 41.13% as neutral, and 33.49% as positive. Conversely, TextBlob demonstrates a different distribution, with 8.59% classified as unfavorable, 64.12% as neutral, and 27.29% as positive. These contrasting distributions highlight the variability in sentiment classification approaches and underscore the importance of selecting appropriate algorithms for accurate sentiment analysis within digital political communication contexts. Such insights enable researchers to understand better the nuances of sentiment expressed within the analyzed content and inform the development of more precise analytical models for interpreting public opinion and emotional dynamics in online discourse.

Meanwhile, social networks are evaluated based on indegree centrality, a metric measuring the number of incoming connections or links directed toward a particular node. This evaluation approach provides insights into the prominence and influence of individual users or entities within the social network, as nodes with higher indegree

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centrality are often perceived as more influential or central in information dissemination and network dynamics. By assessing indegree centrality, this research identifies key opinion leaders, information brokers, and influential nodes within the social network, facilitating a deeper understanding of communication patterns, information flow, and network structure. Consequently, indegree centrality analysis serves as a valuable tool for unraveling the dynamics of digital political communication and elucidating the mechanisms underlying online influence and interaction.

2.2.5 Deployment

The deployment phase of this research entails disseminating and applying findings to relevant stakeholders and real-world contexts. Through deploying research outcomes, policymakers, electoral candidates, and digital platform developers leverage insights gained from toxicity analysis, sentiment classification, and social network analysis to inform evidence-based decision-making processes. By integrating research findings into practice, stakeholders develop strategies to enhance the quality of online political discourse, mitigate the spread of harmful content, and foster greater transparency and accountability in digital communication. Ultimately, the deployment of this research serves as a pivotal step towards realizing the potential for technology to positively impact democratic processes and promote informed civic engagement in the digital age.

3. RESULT AND DISCUSSION

The discussion in this research primarily revolves around toxicity analysis, the implementation of sentiment classification, and social network analysis. Through an in-depth examination of these critical components, this research aims to elucidate the complexities of digital political communication and its impact on societal discourse and democratic processes. By focusing on toxicity analysis, researchers assess the harmfulness and appropriateness of digital content, shedding light on potential risks and ethical considerations within online discourse. Additionally, sentiment classification enables categorizing text-based content into positive, negative, or neutral sentiments, providing insights into the emotional tone and attitudes expressed within the digital discourse. Furthermore, social network analysis allows for exploring interconnected relationships and information flow among users, uncovering patterns of influence and communication dynamics within online communities. This research contributes to a deeper understanding of digital political communication through the comprehensive discussion of these components. It informs evidence-based strategies for promoting healthier and more inclusive online environments.

Based on the results of toxicity analysis, it is discernible that various dimensions of toxicity exhibit different levels of prevalence and severity within the analyzed content. Specifically, the metrics of Toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat present distinct numerical values. For instance, Toxicity is measured at 0.09275 with a severe threshold of 0.98622, while Severe Toxicity is at 0.02508 with a threshold of 0.97866. Identity Attack registers at 0.02520 with a threshold of 0.95906, Insult at 0.06206 with a threshold of 0.96107, Profanity at 0.07786 with a threshold of 0.99911, and Threat at 0.03137 with a threshold of 0.99346. These findings underscore the multifaceted nature of toxicity within online communication and highlight the importance of comprehensive analyses in assessing and addressing potential risks associated with digital political content. Through meticulous examination of these toxicity metrics, researchers can gain valuable insights into the quality of online discourse and inform strategies for promoting healthier and more constructive digital environments.

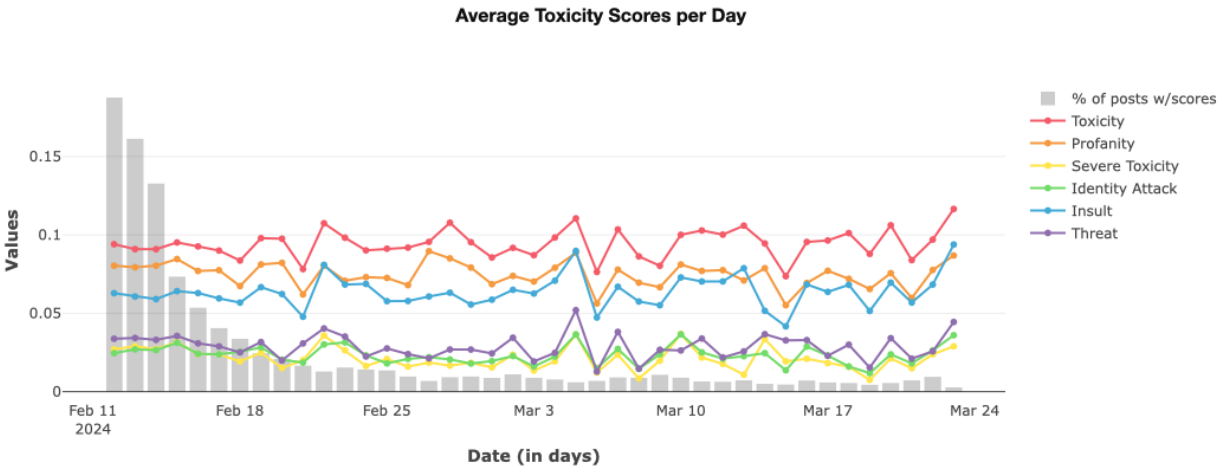

Figure 8. Toxicity Analysis Result (Communalytic)

Figure 8 shows the result of the toxicity analysis. Furthermore, based on the results of sentiment classification, it is evident that different sentiment analysis algorithms exhibit varying patterns across languages. For instance, VADER sentiment analysis for English content shows 25.38% classified as unfavorable, 41.13% as neutral, and

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33.49% as positive sentiments, while TextBlob sentiment analysis for English content displays 8.59% negative, 64.12% neutral, and 27.29% positive sentiments. Interestingly, TextBlob sentiment analysis for French content indicates 1.75% negative, 96.49% neutral, and 1.75% positive sentiments, and for German content, it illustrates 2.00% negative, 96.52% neutral, and 1.48% positive sentiments. These findings highlight the importance of considering language-specific nuances in sentiment analysis and underscore the need for tailored approaches to accurately capture sentiment across diverse linguistic contexts. By recognizing these variations, this research refines sentiment analysis methodologies. It enhances the accuracy of sentiment interpretation in digital political communication across different languages, ultimately contributing to a more nuanced understanding of public sentiment in multilingual online environments.

	# of Posts	Negative Sentiment [-1..-0.05]	Neutral Sentiment (-0.05..0.05)	Positive Sentiment [0.05..1]
VADER (English/EN)	1048	266 (25.38%)	431 (41.13%)	351 (33.49%)
TextBlob (English/EN)	1048	90 (8.59%)	672 (64.12%)	286 (27.29%)
TextBlob (French/FR)	57	1 (1.75%)	55 (96.49%)	1 (1.75%)
TextBlob (German/DE)	1150	23 (2.00%)	1110 (96.52%)	17 (1.48%)

Figure 9. Vader and TextBlob Sentiment Classification

Figure 9 shows the vader and textblob sentiment classification of 2256 out of 24185 posts. Based on the analysis of 2256 out of 24185 posts, it is evident that varying sentiment distributions exist within the examined content. Specifically, 43 posts, constituting 7.30% of the total, exhibit negative sentiments with polarity scores equal to or less than -0.05. Most posts, totaling 360 (61.12%), display neutral sentiments, falling within polarity scores between -0.05 and 0.05. Conversely, 186 posts, accounting for 31.58% of the total, convey positive sentiments with polarity scores equal to or greater than 0.05. These findings underscore the diverse range of sentiments expressed within the analyzed content and highlight the need for nuanced sentiment analysis methodologies to accurately capture the complexities of digital discourse. By recognizing and interpreting these sentiment distributions, this research gains valuable insights into public sentiment and opinion dynamics, informing evidence-based strategies for effective communication and engagement in digital political contexts.

The toxicity and sentiment classification results are effectively visualized through social network analysis, providing a comprehensive understanding of the interplay between harmful content, sentiment dynamics, and network structures within digital communication platforms. This research maps out the dissemination pathways of toxic or emotionally charged content within online communities by integrating toxicity scores and sentiment polarities into user interactions and connections analysis. This visualization approach facilitates the identification of influential nodes, clusters, and communities within the network, shedding light on patterns of information flow, sentiment propagation, and community formation. Through the visual representation of toxicity and sentiment within social networks, researchers can uncover underlying dynamics and relationships, enabling a deeper comprehension of the socio-political implications of digital discourse and guiding the development of targeted interventions to promote healthier online environments.

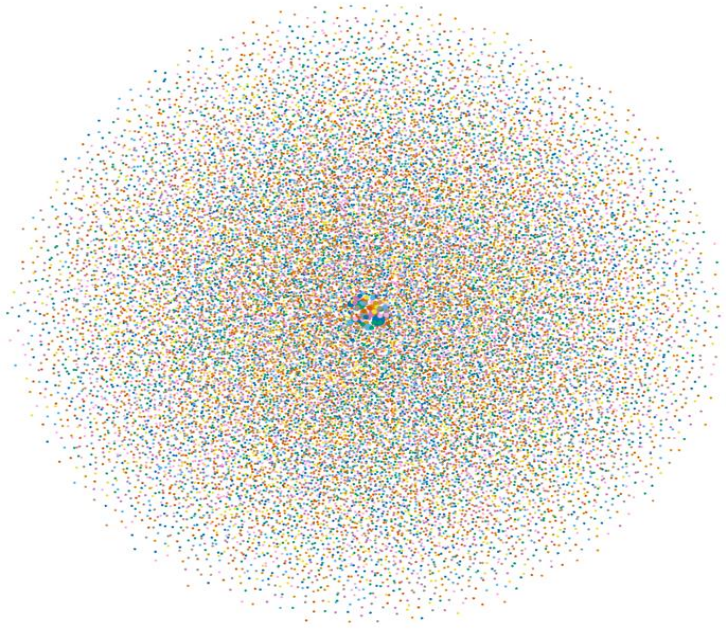

Figure 10. Social Network Reply-To Indegree Centrality (Communalytic)

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Figure 10 shows social network visualization of reply-to-indegree centrality using Communalytic. Based on the visualization of the social network comprising 21842 actor nodes and 106 edges, it becomes evident that the network structure can be tailored to align with the results of sentiment analysis and toxicity assessment. Through carefully mapping actor nodes and edges, researchers can discern patterns of connectivity and clustering that correspond to the sentiment polarity and toxicity levels of digital content. By integrating sentiment and toxicity analysis outcomes into the visualization of the social network, researchers can elucidate the dissemination pathways and community structures associated with different types of content, thereby enhancing understanding of the socio-political dynamics of online discourse. This integration facilitates the identification of influential nodes and communities, informing targeted interventions to mitigate the spread of harmful content and promote healthier digital communication environments.

Toxicity, sentiment classification, and social network analysis constitute integral components of this research, yielding valuable insights into digital political communication. Through toxicity analysis, this research identifies and assesses the prevalence of harmful or inappropriate content, informing strategies for content moderation and fostering healthier online environments. Additionally, sentiment classification enables the categorization of textual content based on emotional tone, providing a nuanced understanding of public sentiment and opinion dynamics. Furthermore, social network analysis elucidates the structure and dynamics of user interactions, uncovering patterns of influence and information dissemination within online communities. Collectively, these analytical approaches generate comprehensive and actionable information, facilitating informed decision-making processes and contributing to advancements in the understanding of digital political communication dynamics.

4. CONCLUSION

In conclusion, this study has provided valuable insights into the dynamics of digital political communication by integrating toxicity analysis, sentiment classification, and social network analysis using the CRISP-DM methodology. The findings underscore the multifaceted nature of online discourse, highlighting the prevalence of harmful content alongside diverse sentiments and complex network structures. The metrics of Toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat present distinct numerical values. For instance, Toxicity is measured at 0.09275 with a severe threshold of 0.98622, while Severe Toxicity is at 0.02508 with a threshold of 0.97866. Identity Attack registers at 0.02520 with a threshold of 0.95906, Insult at 0.06206 with a threshold of 0.96107, Profanity at 0.07786 with a threshold of 0.99911, and Threat at 0.03137 with a threshold of 0.99346. In addition, VADER sentiment analysis for English content shows 25.38% classified as unfavorable, 41.13% as neutral, and 33.49% as positive sentiments, while TextBlob sentiment analysis for English content displays 8.59% negative, 64.12% neutral, and 27.29% positive sentiments. The TextBlob sentiment analysis for French content indicates 1.75% negative, 96.49% neutral, and 1.75% positive sentiments, and for German content, it illustrates 2.00% negative, 96.52% neutral, and 1.48% positive sentiments. These insights have implications for understanding public sentiment, information dissemination, and community formation in online political discourse. By leveraging the findings of this research, policymakers, electoral candidates, and digital platform developers develop evidence-based strategies to promote healthier online environments and foster informed civic engagement. Further research is warranted to explore emerging trends, address methodological challenges, and adapt analytical frameworks to evolving digital communication landscapes. Ultimately, this study contributes to advancing knowledge in digital political communication and underscores the importance of interdisciplinary approaches in addressing contemporary socio-political challenges in the digital age.

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