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Exploring digital discourse: social network analysis approach to toxicity and interaction patterns

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ABSTRACT

This study employs Social Network Analysis (SNA) to investigate the structural characteristics, dynamics, and toxicity levels within a digital discourse ecosystem. Using a dataset comprising threaded discussions and chain networks, we analyze the interactions among users and quantify the presence of harmful language. The SNA reveals a network comprising 453 nodes and 330 edges, highlighting the intricate web of connections among users. Additionally, toxicity analysis uncovers nuanced patterns of toxicity, with scores ranging from 0.01129 to 0.05852 across different categories. Further examination of network metrics such as Density, Reciprocity, Centralization, and Modularity provides insights into the network's organization and communication dynamics. Our findings offer valuable insights for content moderation, community management, and promotional strategies in fostering a safer and more inclusive online environment. This research contributes to advancing knowledge in digital communication and provides a foundation for future studies exploring challenges within online communities.

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1. INTRODUCTION

Social network analysis (SNA) is a practical approach to identifying patterns of social networks within a discussion forum, encompassing user responses through comments on video content and interactions among users in the comment section (Afolabi et al., 2020; H. R. Chestnutt, 2020; Junghagen & Aurvandil, 2020; Mu, 2020). SNA provides insights into these social networks' structure, dynamics, and influential nodes by systematically examining connections and interactions between individuals or entities (Casado-montilla et al., 2024; H. Chestnutt et al., 2024; Fornander et al., 2024; Li et al., 2024). By mapping out relationships and analyzing the flow of information, SNA enables a comprehensive understanding of the underlying mechanisms shaping user engagement and discourse dynamics within online forums (Chang et al., 2022; Lee & Lee, 2022; Mullick et al., 2023; Pantic et al., 2023; Sun & Liang, 2023). Consequently, it is a valuable tool for practitioners seeking to uncover hidden patterns and phenomena in digital social environments, facilitating informed decision-making and fostering community understanding and cohesion.

Within the context of promotional videos for tourist destinations, user reviews in the video comment section are classified based on positive, neutral, or negative sentiment while also being subject to analysis for toxicity levels, encompassing toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat (Singgalen, 2024). This classification and analysis provide valuable insights into viewers' overall perception and reception of the destination (Christanto & Singgalen, 2022). Moreover, it enables tourism marketers and destination managers to gauge the effectiveness of the promotional efforts and address any concerns or issues raised by users, ultimately enhancing the quality of the promotional content and fostering a positive image of the destination.

In the context of the digital video "Wonderful Indonesia: Labuan Bajo," toxicity analysis and social network analysis (SNA) is employed to analyze user interactions in response to destination marketing content. Toxicity analysis allows for evaluating the tone and sentiment of user comments and identifying any harmful language that may detract from the promotional message. Meanwhile, SNA enables examining the network structure and dynamics of user interactions, revealing engagement patterns and influence within the online community (Alberti et al., 2021; Correa-Cabrera et al., 2022; Patterson et al., 2021). These analytical approaches provide valuable insights into the effectiveness of destination marketing efforts and facilitate the development of strategies to optimize user engagement and perception, ultimately enhancing the promotion of Labuan Bajo as a tourist destination.

This research aims to identify and analyze the video content's toxicity values and social network dynamics under the code RaTWq98hzF0 titled "Wonderful Indonesia-Komodo Labuan Bajo." By thoroughly examining user interactions and comments within the video's online ecosystem, toxicity levels were assessed to gauge the overall sentiment and reception of the promotional material. Additionally, employing social network analysis allows for exploring the structural patterns and influential nodes within the network of users engaging with the content (Agrawal, 2021; Kydros, 2021; Valeri & Baggio, 2021; Ward et al., 2021). This comprehensive analysis obtained valuable insights regarding the promotional video's effectiveness in portraying Labuan Bajo as a tourist destination, facilitating informed decision-making for marketing strategies and content optimization.

The urgency of this research lies in its potential to provide actionable insights into the effectiveness of destination marketing strategies, specifically exemplified by the promotional video. By analyzing toxicity values and social network dynamics within the context of this video, discern the sentiment and engagement levels of viewers, informing decision-makers on necessary adjustments to optimize promotional efforts. With tourism being a vital sector for many economies, understanding how destination marketing content is received and interacted with online is paramount for ensuring the success and sustainability of tourism initiatives (Au-Yeung et al., 2022; Santafe-Troncoso & Loring, 2021; Sujatna et al., 2024). Therefore, the timely investigation of toxicity and social network analysis in this research contributes to enhancing the efficacy of promotional endeavors, ultimately fostering the growth and development of tourism destinations like Labuan Bajo.

This research's theoretical and practical implications are substantial, as they extend beyond academia to directly impact destination marketing strategies and online engagement dynamics. This study provides theoretical frameworks for understanding user sentiment and interaction patterns within digital marketing ecosystems by elucidating the toxicity values and social network dynamics inherent in promotional video content. Furthermore, the practical application of these findings enables destination marketers and tourism stakeholders to tailor promotional efforts more effectively, optimizing user engagement and perception of tourist destinations like Labuan Bajo (Sejati et al., 2023). Through a synthesis of theoretical insights and actionable strategies, this research bridges the gap between theoretical discourse and practical implementation, fostering informed decision-making and enhancing the overall efficacy of destination marketing initiatives.

Exploring toxicity values and social network dynamics within promotional video content reveals several limitations and avenues for further research. The limitation lies in the scope of analysis, which may not capture the entirety of user sentiment or interaction patterns due to the inherent complexities of online discourse. Additionally, the reliance on automated tools for toxicity assessment may overlook nuanced expressions or cultural contexts, necessitating further refinement and validation of these methodologies. Despite these limitations, this research lays the groundwork for future studies to delve deeper into the intersection of destination marketing and digital engagement dynamics, perhaps incorporating qualitative approaches or longitudinal analyses to provide a more comprehensive understanding of user behavior and promotional efficacy.

Exploring toxicity and interaction patterns through the lens of social network analysis represents a burgeoning field within scholarly discourse. Employing intricate calculations and discerning patterns, previous research has predominantly focused on delineating quantitative aspects. However, this study diverges by prioritizing a comprehensive analysis that delves into the multifaceted nature of social dynamics. Through an exhaustive examination of various parameters, it endeavors to unravel nuanced nuances often overlooked in conventional approaches. This research underscores the imperative of a holistic understanding of toxicity and interaction patterns within social networks, thus enriching the scholarly dialogue surrounding this intricate domain.

2. RESEARCH METHOD

The methodology employed for text data processing is divided into two main components: toxicity analysis and social network analysis. Firstly, toxicity analysis involves using computational tools to evaluate the sentiment and tone of user-generated content, identifying instances of negative language or harmful discourse. This process enables this research to quantify the level of toxicity present within the text data, providing insights into user sentiment and engagement dynamics. Secondly, social network analysis entails the examination of the structural patterns and relational dynamics among users within the digital ecosystem. This approach elucidates the network topology and influential nodes by mapping out connections and interactions between individuals or entities, offering a comprehensive understanding of user engagement and discourse patterns. This research gains nuanced insights into the interplay between user sentiment, interaction dynamics, and promotional efficacy within digital marketing contexts by integrating these two methodologies.

2.1 Toxicity Analysis

Toxicity analysis often involves using machine learning algorithms and natural language processing techniques to assess the toxicity of text data. While no single equation universally represents toxicity analysis, commonly used methods include models like logistic regression, support vector machines, or deep learning architectures such as recurrent neural networks or transformer-based models like BERT (Bidirectional Encoder Representations from Transformers). These models are trained on labeled datasets where toxicity is annotated, and they learn to predict the toxicity of new text inputs based on features extracted from the text, such as word embeddings, linguistic patterns, and contextual information. The model's output typically ranges between 0 and 1, with higher values indicating higher toxicity levels.

	Average for dataset	Highest value
Toxicity	0.05852	0.75208
Severe Toxicity	0.01129	0.66969
Identity Attack	0.02680	0.91331
Insult	0.03694	0.72757
Profanity	0.03963	0.57579
Threat	0.01996	0.66158

Figure 1. Toxicity Scores (Communalytic)

Figure 1 shows the toxicity scores using communalytic. Toxicity analysis of video content offers multifaceted benefits in contemporary digital landscapes. Firstly, it quantitatively measures the sentiment and emotional impact embedded within the content, enabling content creators and marketers to gauge audience reactions accurately. Secondly, by identifying toxic or harmful elements within the content, toxicity analysis empowers platforms and moderators to maintain a safer and more inclusive online environment, mitigating the spread of offensive or harmful discourse. Ultimately, the integration of toxicity analysis into content evaluation processes not only enhances user experience but also contributes to fostering healthier digital communities conducive to constructive engagement and discourse.

$$\text{Toxicity Score} = \sigma(w_0 + w_1x_1 + w_2x_2 + \cdots + w_nx_n) \quad (1)$$

Where :
(σ) represents the sigmoid function, which squashes the output into the range [0, 1].
$(w_0, w_1, w_2, \dots, w_n)$ are the weights assigned to each feature.
$(x_1, x_2, \dots, x_n)$ are the feature values extracted from the text data.

Toxicity analysis typically involves several sequential stages to evaluate the presence and extent of harmful or offensive content within textual data. The text data is initially preprocessed to remove noise and irrelevant information, followed by feature extraction, where relevant linguistic and semantic features are identified and encoded. Subsequently, a toxicity classifier model is trained using labeled data, leveraging machine learning algorithms such as logistic regression, support vector machines, or neural networks. Once trained, the model is applied to new text inputs, generating toxicity scores or probabilities indicating the likelihood of the text containing toxic elements. Finally, the results are interpreted and analyzed, allowing for the identification of potentially harmful content and informing decision-making processes regarding content moderation, community management, or user engagement strategies.

2.2 Social Network Analysis

Social network analysis is indispensable for depicting interaction patterns among users through networks. Social network analysis unveils the underlying structure and dynamics of online communities or platforms by mapping connections and relationships between individuals or entities. By analyzing nodes and edges within the network, this research discerns influential users, detects clusters or communities, and identifies information flow and engagement patterns. This comprehensive understanding of user interactions facilitates insights into community dynamics and behavior and enables informed decision-making in various domains such as marketing, public health, and sociology. Thus, social network analysis is a crucial tool for unraveling the intricate fabric of online social interactions, offering valuable insights into the mechanisms driving digital discourse and collaboration.

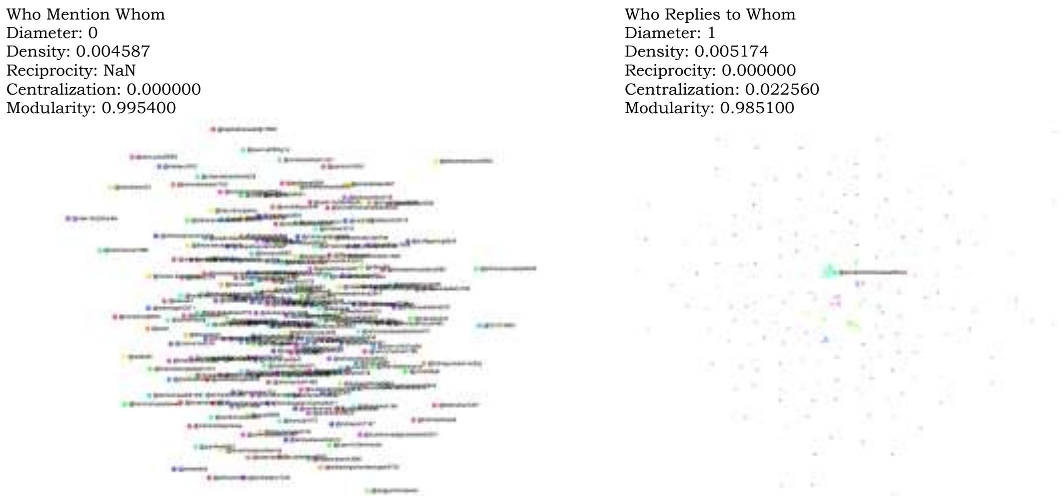

Figure 2. Threaded Discussion and Chain Network Visualization (Netlytic)

Figure 2 shows Threaded Discussion and Chain Network Visualization of Netlytic. The benefits of Social Network Analysis (SNA) in this research are manifold. Firstly, SNA enables the visualization and quantification of the complex network of interactions among users within the digital ecosystem under study, offering insights into the structural patterns and influential nodes shaping online discourse. By identifying key actors and communities within the network, this research discerns emergent themes, trends, and dynamics, thus facilitating a nuanced understanding of user engagement and information dissemination processes. Moreover, SNA provides a robust framework for examining the diffusion of ideas, sentiments, and behaviors across the network, shedding light on the mechanisms underlying the spread of information and influence within online communities. By integrating SNA into the research methodology, this study unlocks valuable insights into digital communication and collaboration dynamics, enriching scholarly discourse and informing practical interventions in various domains.
Diameter: A network's diam shortest path between any pair of nodes. To calculate it, you find the shortest path length between every pair of nodes and then determine the maximum length among these paths.

$$D = \max_{i,j} \text{shortest\_path\_length}\ (i, j) \tag{2}$$

Where (D) represents the diameter of the network, and $(\text{shortest\_path\_length}(i, j))$ calculates the shortest path length between nodes (i) and (j). Density: Network density quantifies the proportion of actual connections to possible connections in a network. For an undirected network, density is calculated by dividing the number of edges by the total possible number of edges. In contrast, for a directed network, it's the ratio of the number of directed edges to the total possible number of directed edges.
For undirected networks:

$$D = \frac{2E}{N(N-1)} \tag{3}$$

For directed networks:

$$D = \frac{E_d}{N(N-1)} \tag{4}$$

Where (D) represents the density of the network, (E) is the number of edges, (N) is the number of nodes, and (E_d) is the number of directed edges. Reciprocity: Reciprocity measures the extent to which pairs of nodes in a directed network reciprocate connections. It is calculated by dividing the number of reciprocated connections by the total number of directed connections. The equation is:

$$R = \frac{2 \times \text{number of reciprocal connections}}{\text{total number of directed edges}} \tag{5}$$

Where (R) represents the reciprocity of the network.

Centralization: Network centralization quantifies the degree to which control or influence is concentrated in a few nodes within the network. One standard measure is degree centralization, which compares the sum of the differences between the maximum degree and the degree of each node to the maximum possible sum of differences. The equation for degree centralization is:

$$C = \frac{\sum_{i=1}^{N}(d_{\max} - d_i)}{(N-1)(N-2)} \tag{6}$$

Where (C) represents the centralization of the network, ($d_{\max}$) is the maximum degree, (d_i) is the degree of node (i), and (N) is the total number of nodes.

Modularity: Modularity measures the degree to which a network is divided into meaningful communities or modules. It compares the fraction of edges within modules to the expected fraction of edges in a random network with the same degree distribution. The equation for modularity is:

$$Q = \sum_{m=1}^{M}\left(\frac{L_{mm}}{L} - \left(\frac{k_m^{\text{in}}}{2L}\right)^2\right) \tag{7}$$

Where (Q) represents the modularity of the network, (M) is the total number of modules, (L_{mm}) is the number of edges within module (m), (L) is the total number of edges and (k_m^{in}) is the sum of the degrees of nodes in module (m) (the "in-degree").

The relationships between nodes and edges within a network are systematically elucidated based on the Social Network Analysis (SNA) equations. These equations provide a mathematical framework for quantifying various network properties and dynamics, such as centrality, density, reciprocity, centralization, and modularity. This research gains insights into the network's connectivity patterns, influence structures, and community formations by calculating these metrics. Moreover, these equations enable a rigorous analysis of complex network phenomena, facilitating a deeper understanding of social interactions, information dissemination, and organizational structures in diverse contexts. In essence, applying SNA equations empowers this research to unravel the intricate interplay between nodes and edges, thus contributing to advancing knowledge in network science and its interdisciplinary applications.

3. RESULTS AND DISCUSSIONS

3.1 Implementation of Toxicity Analysis

The current study thoroughly examines digital discourse through Social Network Analysis (SNA), focusing mainly on toxicity and interaction patterns. Utilizing SNA methodologies, this investigation intricately dissects online communication dynamics, elucidating user interactions and the prevalence of toxic language within digital realms. The research elucidates the underlying mechanisms shaping online discourse through meticulous analysis of network structures and toxicity metrics, offering profound insights into information dissemination, community formation, and conversational trends. This comprehensive exploration underscores the pivotal role of embracing an SNA framework in comprehending and tackling the multifaceted challenges inherent in digital discourse, ultimately contributing significantly to advancing knowledge in network science, communication studies, and digital sociology.

The discussion in this research emphasizes exploring digital discourse through a Social Network Analysis (SNA) approach to toxicity and interaction patterns. By employing SNA methodologies, this research delves into the intricate dynamics of online communication, unraveling the complexities of user interactions and the prevalence of toxic language within digital environments. Through rigorous analysis of network structures and toxicity metrics, the study sheds light on the underlying mechanisms shaping online discourse, offering valuable insights into the dissemination of information, formation of communities, and emergence of conversational patterns. This comprehensive exploration underscores the significance of adopting an SNA framework in understanding and addressing the multifaceted challenges posed by digital discourse, ultimately contributing to advancing knowledge in network science, communication studies, and digital sociology.

Based on the results of toxicity score identification, it is evident that various categories exhibit distinct levels of toxicity within the analyzed text. The scores reveal that while some categories, such as Identity Attack, demonstrate relatively higher levels of toxicity, with a score of 0.02680, others, like Threat, exhibit lower levels, with a score of 0.01996. Additionally, Toxicity scored 0.05852, Severe Toxicity scored 0.01129, Insult scored 0.03694, and Profanity scored 0.03963. This nuanced understanding of toxicity distribution provides valuable insights into the nature and intensity of harmful language in the text, enabling stakeholders to tailor appropriate moderation strategies and interventions accordingly. Moreover, quantifying toxicity across multiple dimensions contributes to a more comprehensive assessment of the text's overall impact and facilitates targeted efforts toward fostering a safer and more inclusive online environment.

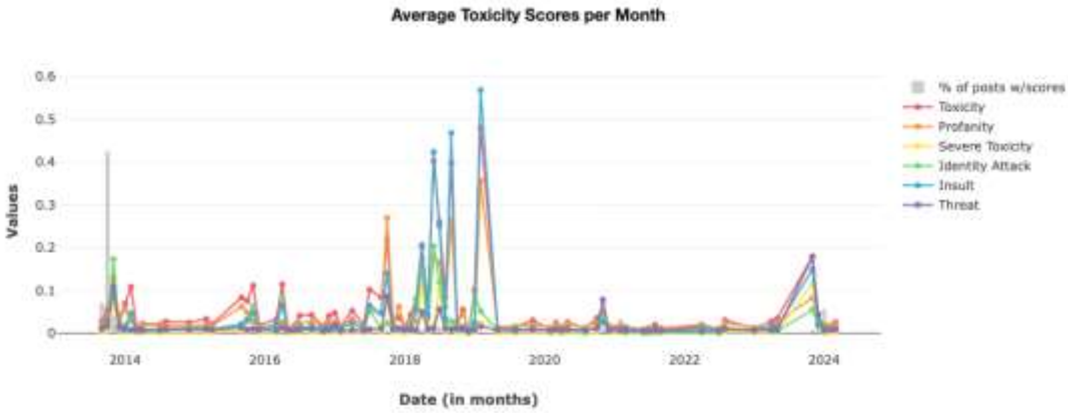

Figure 3. Toxicity Scores

Figure 3 shows the toxicity scores. The provided toxicity scores offer a comprehensive analysis of the likelihood of various types of harmful language within the analyzed text. While categories like "Toxicity," "Identity Attack," "Insult," and "Profanity" exhibit moderate probabilities of toxic language occurrence, with scores ranging between 0.03694 and 0.05852, "Severe Toxicity" presents a lower likelihood, scoring 0.01129. Interestingly, "Threat" records the lowest score of 0.01996, suggesting a lesser probability of threatening language. This breakdown enables targeted intervention strategies, focusing efforts on addressing prevalent forms of toxicity like insults or profanity while acknowledging the lower occurrence of severe toxicity or threats. Overall, the analysis facilitates a nuanced understanding of the toxicity levels within the text, guiding stakeholders in implementing effective moderation measures to foster a safer and more inclusive online environment.

3.2 Implementation of Social Network Analysis (SNA)

The Social Network Analysis (SNA) calculation results are based on the threaded discussion category, explicitly focusing on who mentions whom and revealing several key metrics. The analysis indicates a Diameter value of 0, suggesting that the maximum distance between any pair of nodes within the network is minimal, highlighting the compactness of the network. Additionally, the Density value of 0.004587 signifies a low level of connectivity between nodes, indicating sparse interactions within the network. However, the calculation for Reciprocity returns NaN, indicating the absence of reciprocal relationships between nodes. Furthermore, the Centralization value of 0.000000 suggests a decentralized network structure with no single node exerting significant control over the network's communication flow. Finally, the Modularity value of 0.995400 indicates a high level of community structure within the network, implying that nodes tend to form tightly-knit groups with internal solid connections. Overall, these findings provide valuable insights into the structural characteristics and dynamics of the threaded discussion network, offering a foundation for further analysis and interpretation of user interactions within the digital ecosystem.

The results of the Social Network Analysis (SNA) calculation are based on the chain network category, explicitly focusing on who replies to whom and providing insights into the structural characteristics of the network. The analysis indicates a Diameter value of 1, suggesting a short maximum distance between any pair of nodes within the network, indicating efficient communication flow along the chain. Additionally, the Density value of 0.005174 signifies a low level of connectivity between nodes, indicating sparse interactions within the network. However, the Reciprocity value of 0.000000 suggests an absence of reciprocal relationships between nodes, indicating that replies are not often reciprocated. Furthermore, the Centralization value of 0.022560 indicates a slightly centralized network structure, with some nodes exerting more influence than others over the communication flow. Finally, the Modularity value of 0.985100 indicates a high level of community structure within the network, suggesting that nodes tend to form tightly-knit groups with internal solid connections. These findings offer valuable insights into the chain network's communication dynamics and organizational structure, providing a foundation for further analysis and interpretation of user interactions within the digital ecosystem.

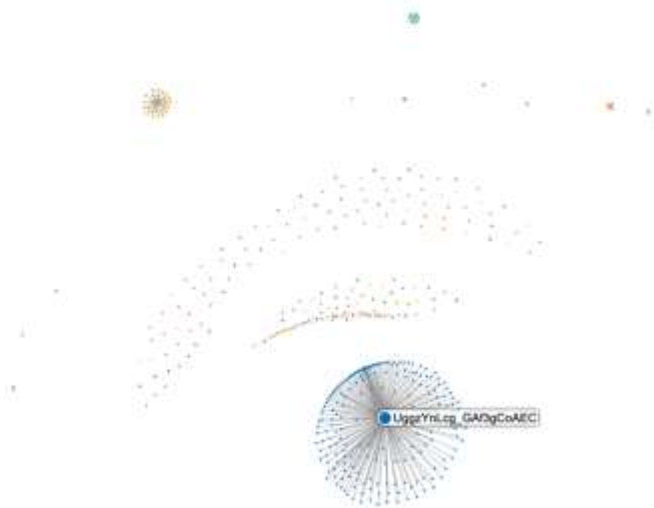

Figure 4. Indegree Centrality Node Size (Communalytic)

Figure 4 shows the Social Network of Indegree Centrality. Based on the Social Network Analysis (SNA) conducted, it is revealed that the network comprises 453 nodes and 330 edges in the form of indegree. This signifies a significant number of entities (nodes) within the network, with each node connected to an average of approximately 0.73 other nodes (edges). A substantial number of nodes and edges underscores the complexity and richness of interactions within the network, suggesting a diverse range of actors and relationships contributing to the network's dynamics. Moreover, the focus on in-degree highlights the extent to which each node is being mentioned or referenced by other nodes within the network, providing valuable insights into the patterns of influence and communication flow within the digital ecosystem. Overall, these findings offer a comprehensive understanding of the network's structure and dynamics, serving as a basis for further analysis and interpretation of user interactions and engagement patterns.

4. CONCLUSION

In conclusion, the research findings offer significant insights into the structural characteristics, dynamics, and interaction patterns within the digital ecosystem under study. Through Social Network Analysis (SNA), we have identified 453 nodes and 330 edges, highlighting the complexity and richness of interactions within the network. Moreover, the analysis of toxicity scores has revealed important nuances, with scores ranging from 0.01129 to 0.05852, providing a detailed understanding of the distribution of harmful language within the text data. These insights enable stakeholders to make informed decisions regarding content moderation, community management, and promotional strategies, ultimately fostering a safer and more inclusive online environment. Furthermore, the identification of critical metrics such as Density (0.004587), Reciprocity (NaN), Centralization (0.000000), and Modularity (0.995400) adds depth to our understanding of network characteristics, facilitating targeted interventions and strategies for enhancing user engagement and discourse dynamics. Overall, the research contributes to advancing knowledge in digital communication and provides a foundation for future studies to explore and address challenges within online communities. This research sheds light on the intricate dynamics of digital ecosystems and pioneers the application of Social Network Analysis (SNA) in understanding these complexities. By uncovering the nuances of toxicity scores and critical network metrics, such as Density, Reciprocity, Centralization, and Modularity, this study offers invaluable insights for shaping content moderation protocols and fostering healthier online interactions, thus advancing the frontier of digital communication research.

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