Visual Methods for Network Analytics of Echo Chamber: A Case Study of Thailand's General Election 2023

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Abstract: This research develops visual methods to study the echo chamber effect through a case study on Thailand's 2023 General Election. Using visualization techniques like node-link diagrams, t-SNE projections, and heatmaps, it examines homophilic relationships, clustering, and polarization in online communities. To minimize inaccuracies and biases, network graphs are created from contextual analysis of user-generated content, rather than relying on predefined relationships like friendships or followers. The study applies the Echo Chamber Score (ECS) with visualizations to explore variations in analytical methods and how they capture different aspects of echo chambers. Additionally, it illustrates how political events shape online discourse and community dynamics by linking ECS with key political milestones.

1 INTRODUCTION

The rise of social media has intensified echo chambers, where selective exposure reinforces pre-existing beliefs, promoting polarization, misinformation, and conspiracy theories. Platforms like Twitter, Facebook, and Pantip amplify these effects, particularly during events like Thailand's 2023 General Election (Vicario et al., 2016)(Unerman, 2020).

This study employs network-based analytical methods to examine echo chamber formation. It constructs network graphs based on user-generated content, semantic similarity, and shared opinions, utilizing visualization techniques such as node-link diagrams, t-SNE projections, and heatmaps, alongside the EchoGAE model (Alatawi et al., 2023).

By analyzing graph construction methodologies and external influences, this research integrates computational social science with visual analytics to provide insights into selective exposure and polarization. The findings offer a structured approach to understanding echo chambers and their societal impact.

2 RELATED WORK

This section discusses key studies in network graph analysis, homophilic interactions, and echo chambers, focusing on methods used to study ideological polarization in political discussions.

2.1 Echo Chamber

An echo chamber is an environment where selective exposure reinforces beliefs, limiting diverse perspectives and amplifying confirmation bias (Cinelli et al., 2021)(Jiang et al., 2021). Social media exacerbates this effect by directing users to supportive content (Vicario et al., 2016). Events like the 2016 USA election demonstrated how echo chambers distort perceptions (Guo et al., 2018), though awareness of the issue slightly reduced their effect by 2020 (Yang et al., 2020)

Traditional approaches to quantifying echo chambers rely on modularity analysis, random walkers, and opinion-spreading models (Markgraf and Schoch, 2019)(Cota et al., 2019), but these often require extensive ideological labeling. EchoGAE, a Graph Autoencoder-based model, overcomes this limitation by generating embeddings that integrate content-based similarity with network structure, allowing for scalable analysis of polarization (Alatawi et al., 2023). Another approach to studying echo chambers is through signals like polarization, which leads to ideologically segregated communities. These can be detected using methods such as the Louvain algorithm and visualized with density plots and clustering techniques (Conover et al., 2011)(Botte et al., 2022), which are often more interpretable compared to machine learning methods like EchoGAE. This study builds on previous work by combining network analysis to interpret echo chamber signals and employing EchoGAE to analyze clustering, homophilic interactions, and ideological segregation

2.2 Network Graph Construction

Earlier social network research focused on predefined relationships (Goodreau et al., 2009), but recent work emphasizes contextual interactions (Mcpherson et al., 2001)(Goel et al., 2019). Textual analysis methods like LDA and k-means clustering reveal patterns in user interactions (Hoque and Carenini, 2014). While deep learning models like Sentence-BERT offer precise insights (Reimers and Gurevych, 2019), this study balances efficiency and interpretability by using LDA and k-means to explore thematic clustering.

2.3 Visualization for Echo Chamber Analysis

Visualization reveals patterns in complex network data. Node-link diagrams, force-directed layouts, and hybrid techniques like Nodetrix (Henry et al., 2007) highlight community structures. Visual analytics integrates computational methods with interactive visualization (Thomas and Cook, 2005). Tools like SocialOcean facilitate interaction analysis(Diehl et al., 2018), while t-SNE visualizations highlight ideological clustering and polarization(van der Maaten and Hinton, 2008). This study uses basic visualization techniques to analyze network graphs, support echo chamber exploration, and incorporate EchoGAE into visual analytics to examine polarization and variations in graph construction.

3 DESIGN REQUIREMENT ANALYSIS

This study designs visual methods for echo chamber analysis. The visualizations should provide insights based on the following requirements.

Network Graph Characteristics. The goal of this visualization design is to explore the structure of network graphs and address key questions, such as: *What does the network graph look like? Are there observable patterns indicative of echo chamber effects?* To capture echo chambers effectively, network graphs must reflect homophilic interactions—users interacting with others who share similar attributes, such as ideologies or opinions. This tendency, known as homophily, is central to echo chamber dynamics, as users reinforce each other's views and isolate dissenting opinions (Mcpherson et al., 2001). Differences in construction methods reveal unique characteristics, aiding method selection.

Echo Chamber Effect. Building on the exploration of echo chamber signals in network graphs, the next question is: *How do user attributes influence the ability to capture echo chambers?* To answer this, the EchoGAE embedding model is employed. Visualizing user embeddings enhances understanding of the network while incorporating user attributes. The visualizations should enable researchers to explore how network characteristics, such as homophily, and embedded node attributes contribute to echo chamber formation. Success will be measured by how clearly the visualizations reveal clustering patterns and interactions aligned with echo chamber phenomena.

News Influence on Echo Chamber Formation. This research also examines how factors, particularly news events, affect echo chamber formation. Although algorithms are not considered here, it is assumed that echo chambers are more likely to form when discussions attract significant attention, beyond just topic categorization (e.g., controversial vs. non-polarized topics) (Alatawi et al., 2023). This section focuses on how key news events, varying in attention and impact, influence echo chamber development. The visualizations will demonstrate how news events contribute to the formation and intensity of echo chambers by tracking monthly events and quantifying their effects.

4 VISUALIZATION

This section details the visual methods applied to network structures, following the design framework.

4.1 Network Graph Structure Overview

Network graphs are powerful tools for studying the structural patterns and dynamics of social interactions, offering insights into user behaviors, community formations, and the prevalence of homophilic relationships. By visualizing these interactions, researchers can uncover the underlying structure of social networks and examine how connections between individuals shape broader patterns of discourse and group behavior.

Network Graph Structure. Node-link diagrams reveal network patterns. In Figure 1, nodes represent users, and edges indicate homophilic interactions. Densely connected clusters suggest stronger echo chambers.

Community Structure This visualization is introduced to examine community structure patterns. The Louvain algorithm identifies communities (Figure 3), with nodes representing groups, edges showing inter-community interactions and nodes colors indicate the number of users in group. This highlights ideological clustering and reveals how different methods capture network structures.

Method Comparison. Comparing network graph construction methods ensures accurate homophilic relationship representation. A sequence of visualizations examines structural differences, accompanied by a bar chart quantifying unique and common edges. Figure 4.

4.2 Echo Chamber Effect View

For echo chamber exploration, the EchoGAE model is utilized to embed user attributes into node representations. A t-SNE plot is employed to project high-dimensional user interaction data into a two-dimensional space (Figure 5), facilitating the visualization of clustering patterns associated with the echo chamber effect. Each point in the plot represents a user, with spatial proximity indicating similarity in interactions or opinions. Users who cluster closely together are likely to share similar viewpoints or engage frequently, potentially forming echo chambers.

This visualization is adapted from (Alatawi et al., 2023), where the t-SNE method was applied to illustrate clustering patterns after embedding node attributes using EchoGAE. The results reveal clustering tendencies, where dense, isolated clusters suggest strong echo chambers, while overlapping or loosely connected clusters may indicate weaker echo chambers or more diverse interactions.

4.3 News Influence on the Formation of Echo Chambers

The visualizations discussed thus far focus on identifying echo chamber signals and analyzing network graph characteristics to support method selection. In contrast, this visualization examines factors related to echo chambers using the Echo Chamber Score (ECS), with a focus on news and events. A heatmap (Figure 6) is used to compare the engagement levels of key events with the ECS over time, exploring the potential impact of news events on echo chamber formation.

5 EVALUATION

In this section, the effectiveness and usability of the visual methods are demonstrated through case studies, using Thailand's 2023 General Election discussion data from Pantip. This dataset was selected as it provides real-world discourse on a widely discussed event. While political events often involve diverse perspectives and varying degrees of polarization, the analysis in this study remains methodologically driven, focusing on the structural and behavioral patterns within the data rather than making normative judgments. The use of real-world data highlights the practical applicability of the proposed methods in examining online discourse dynamics in an empirical context.

5.1 Political Polarization and Ideological Echo Chambers

The case study examines ideological polarization in the Rajdumnern forum discussions during the election. The dataset includes 10,771 posts and 150,487 comments, embedded using WangchanBERTa (Lowphansirikul et al., 2021) to capture semantic meaning. A network graph was constructed with nodes as users and edges indicating agreement or alignment, representing homophilic interactions.

Two techniques, *k*-means and Latent Dirichlet Allocation (LDA), were applied to group users based on semantic similarity. Networks were then created from two distinct relationship definitions, each designed to capture homophilic interactions:

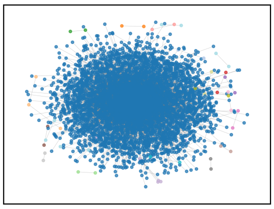
Semantic Agreement Connectivity(SAC): An edge is established if a user's comment belongs to the same cluster as the original post, indicating direct semantic agreement on political content. This approach assumes that homophilic interactions arise from users responding to posts.

Interactive Alignment Connectivity(IAC): Based on web forum behavior, an edge is formed if two users comment on the same post and their comments cluster together. This treats comments as content nodes, capturing indirect alignment among commenters.

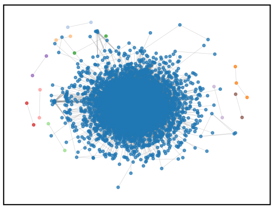
By combining these two clustering techniques with the two relationship definitions, four distinct network graphs were generated, each providing a unique perspective on user alignment. This approach enables a comprehensive comparison of how different clustering methods and relationship definitions influence network construction, offering nuanced insights into ideological polarization.

5.1.1 Identifying Ideological Polarization Through Network Structure

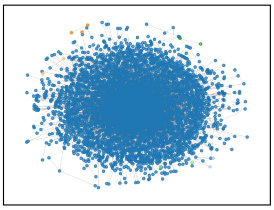
The node-link diagram in Figure 1 illustrates the network structure, where nodes represent users and edges indicate homophilic interactions based on political opinion alignment. A central cluster dominates all graphs, reflecting a high concentration of users with similar viewpoints and reinforcing the echo chamber effect.



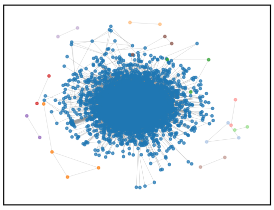
(a) *k*-means-SAC



(b) *k*-means-IAC



(c) LDA-SAC



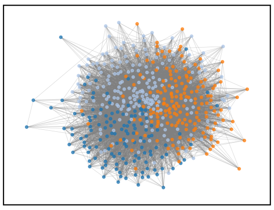
(d) LDA-IAC

Figure 1: Comparison of Network Graphs Using Four Different Methods.This figure presents network graphs constructed using two clustering methods (*k*-means and LDA) and two relationship definitions (SAC and IAC). The colors represent the network group to which each node belongs based on its connections.

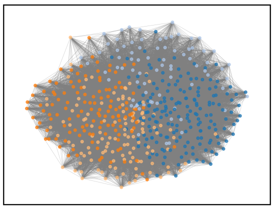
Graphs from SAC further highlight this trend, showing users gravitating toward shared content, which aligns with selective exposure issues reported in prior research (Barberá et al., 2015). Smaller, isolated groups at the edges likely represent users with differing opinions or less frequent interactions, while the dense center indicates high engagement among like-minded users.

To analyze ideological polarization, the Louvain algorithm was applied for community detection, visualized in Figure 1. Given the complexity of large networks, only the top 500 highest-degree nodes were selected to improve readability and interpretability.

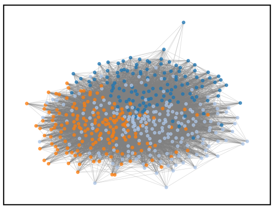
The Louvain algorithm revealed multiple communities within the assumed central cluster, weakening its cohesion Figure 2. It is suggests a fluid network structure rather than strongly separated ideological groups. High-centrality nodes act as bridges, indicating that echo chambers may form through information flow rather than strict divisions. These findings challenge the assumption that a dense central cluster represents an echo chamber, highlighting the role of selective engagement and issue-based agreement in shaping ideological divisions.



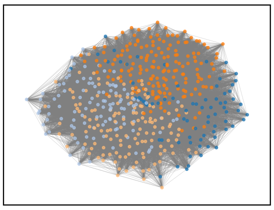
(a) *k*-means-SAC



(b) *k*-means-IAC



(c) LDA-SAC



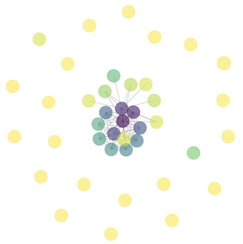
(d) LDA-IAC

Figure 2: Network Community Structure Focusing on High-Degree Nodes. This figure displays subgraphs consisting of the top 500 high-degree nodes from the network. The nodes are colored based on the community they belong to, as detected using the Louvain algorithm.

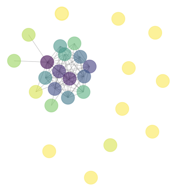
Real data analysis reinforces these findings, showing that ideological divisions are complex and issue-based rather than strictly partisan. While LDA-SAC highlights community separation, engagement patterns suggest political alignment is fluid, with users selectively agreeing on policies rather than adhering strictly to party lines. This leads to overlapping communities rather than entirely isolated ideological clusters.

Overall, these visualization meets the key requirements and provides a comprehensive view of the data. However, it lacks clear differentiation when comparing the various methods. Additionally, handling large datasets presents a challenge, and the visualization could be further enhanced to address this limitation, ultimately improving its effectiveness and scalability(von Landesberger et al., 2011).

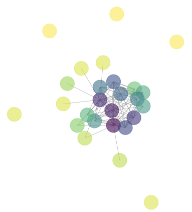
To confirm ideological polarization and explore signs of the echo chamber effect, the Community Structure visualization was applied to visualize connections between communities, and the number of users within each community (Figure 3).



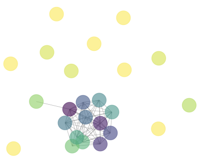
(a) k-means-SAC



(b) k-means-IAC



(c) LDA-SAC



(d) LDA-IAC

Figure 3: Visualization of Community Relationship in Network Graphs. This figure presents an interactive network graph, showing cluster relationships for each construction method. Nodes represent communities identified by the Louvain algorithm, with colors indicating community size. Edges represent homophilic interactions between users from different communities.

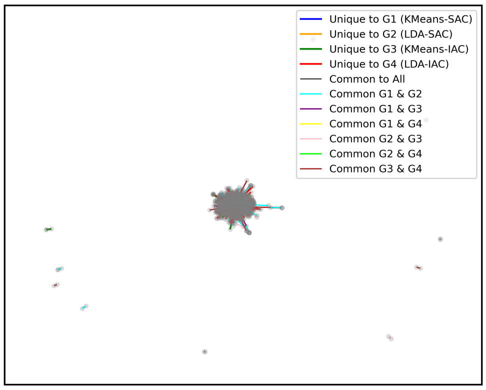
The colors in the visualization represent cluster sizes, with a gradient from purple for the largest clusters to green and yellow for smaller ones. Nodes colored in purple indicate the largest, most central clusters, suggesting they represent the most active groups in the network.

Across methods, k-means-SAC (Figure 3a) shows a hierarchical structure with isolated groups, LDA-SAC (Figure 3c) reveals stronger interconnections, k-means-IAC (Figure 3b) highlights denser core structures, and LDA-IAC (Figure 3d) balances central density and decentralization. Sparse inter-group links across all methods indicate polarization-driven echo chambers.

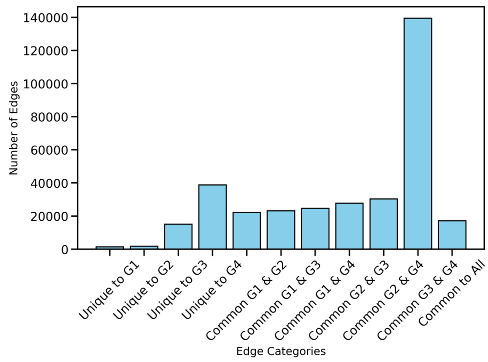
Network structures reflect issue-based homophily rather than strict political divisions. LDA-SAC, capturing ideological clustering through semantic agreement, shows that echo chambers emerge from thematic alignment rather than absolute polarization.

5.1.2 Comparing Structural Patterns Across Methods

Graphs were plotted to compare relationships across the four methods (Figure 4), with edge colors distinguishing unique and shared relationships across 11 characteristics. The bar chart illustrates the distribution of unique and common edges across G1 (k-means-SAC), G2 (LDA-SAC), G3 (k-means-IAC), and G4 (LDA-IAC), revealing structural complexity.



(a) Comparison of Relationship across Four Methods



(b) Edges Counts: Unique and Common Edges Across Graphs

Figure 4: Comparison of Relationships Across Four Methods This figure compares relationships in four network graphs constructed using k-means and LDA clustering under SAC and IAC. The node-link diagram (top) shows the network structure, and the bar chart (bottom) quantifies the distribution of unique and common edges.

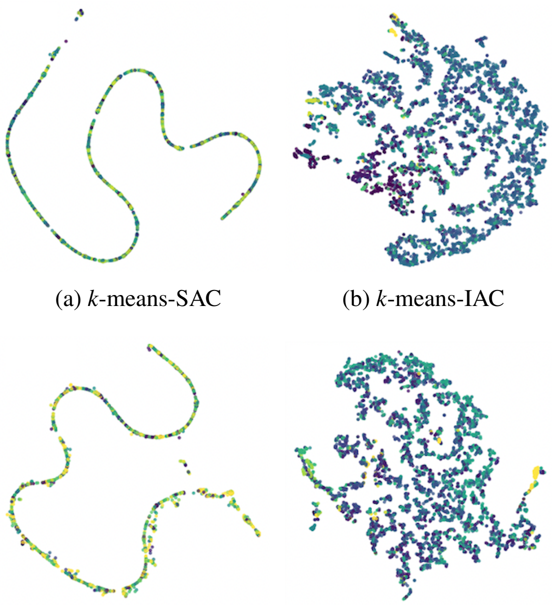
The graph in Figure 4 highlights unique relationships across the four methods, revealing structural complexity. The bar chart displays the number of edges unique to each method (k-means-SAC, LDA-SAC, k-means-IAC, LDA-IAC) and shared edges, offering a clear breakdown of edge distributions.

LDA-IAC captures the most nuanced relationships, as shown by its higher number of unique edges (Figure 4b). The high common-edge count in IAC-based methods (G3, G4) highlights their sensitivity to subtle homophilic connections.

Selecting LDA-SAC balances content-driven coherence with network clarity, effectively capturing semantic-based homophily while maintaining interpretability in network structure.

5.1.3 Exploring Ideological Alignment Using User Embeddings

The Echo Chamber Effect is measured using the EchoGAE model, which requires the network graph (see Section 5.1) and user embeddings, created by averaging 20 posts or comments per user with normalized missing data. These inputs allow the model to assess interactions, with ECS derived from the silhouette score to measure cohesion and separation.



(a) k-means-SAC (b) k-means-IAC

(c) LDA-SAC (d) LDA-IAC

Figure 5: 2D Projections of User Embeddings Across Four Network Graphs. This figure presents the 2D projections (using the t-SNE algorithm (van der Maaten and Hinton, 2008)) of user embeddings from four different network graphs after embedding using EchoGAE algorithm. Colors represent distinct communities.

The analysis of political conversations during Thailand's 2023 general election reveals that SAC-based methods yield lower ECS, with LDA (0.240) forming more homogeneous communities and k-means (0.213) capturing diverse groups. IAC-based methods produce higher ECS, particularly k-means (0.415), indicating stronger polarization, while LDA (0.315) shows moderate polarization. These results highlight how clustering methods shape the echo chamber effect.

The t-SNE visualization (Figure 5a, Figure 5c) shows ideological alignment through a curve-like projection, indicating shared opinions drive user clustering, but ideological alignment is localized around specific topics.

Despite its lower ECS, LDA-SAC was selected for its interpretable structure, capturing issue-based homophily. This choice aligns with prior polarization findings but reveals discrepancies, suggesting that excluding node attributes may have contributed to the inconsistency, requiring further exploration.

5.2 Temporal Analysis of Echo Chamber Dynamics During Key Election Events

Data on key events from January to August 2023 was collected from news articles and social media, focusing on Thailand's general election. Engagement rates were estimated using YouTube view counts from 30 relevant videos, retrieved via the YouTube API with keywords such as "Thailand Election 2023", "Thailand General Election".

Engagement levels—*Very High*, *High*, *Moderate*, and *Low*—were based on log-transformed view counts, with quartiles defining the categories. These classifications reflect public interest and media attention, with major events like the election labeled as Very High engagement, and routine updates as Moderate or Low.

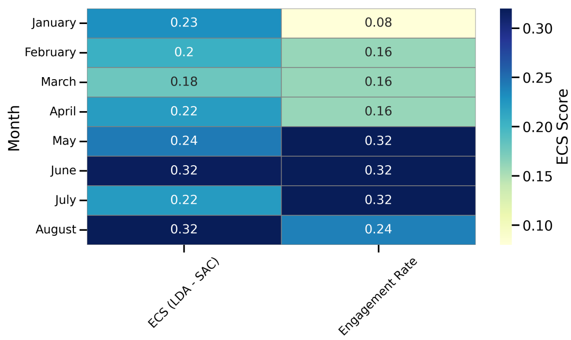


Figure 6: Heatmap of ECS by Month, Showing Engagement Rate Levels Estimated Based on the Importance of Key Events in Thailand's 2023 General Election.

The heatmap (Figure 6) shows ECS by month from the LDA-SAC method, alongside engagement rate levels, which are set as a proportion of the maximum ECS. Four engagement levels—Low, Moderate, High, and Very High—correspond to 25%, 50%, 75%, and 100% of the maximum ECS value.

Despite high engagement during key political events, ECS does not consistently align with engagement levels, suggesting that high engagement does not always lead to stronger ideological polarization. Major events may involve diverse discussions, diluting ideological boundaries. For example, the higher ECS in June and July, despite varying engagement, indicates that specific issues drove stronger alignment, even though they were not discussed uniformly throughout the year.

This highlights how LDA-SAC captures clustering around polarized issues, which may not always correlate with engagement levels. The discrepancy between ECS and engagement suggests that polarization is driven more by discourse focus than by interaction volume. In some cases, lower engagement with focused discussions leads to stronger alignment, while high engagement with diverse topics weakens clustering.

LDA-SAC reflects issue-based homophily, despite fluctuating engagement, justifies its use for analyzing political discourse during Thailand's 2023 election. Its focus on issue-driven discussions makes it a valuable tool for understanding ideological polarization in political events.

6 DISCUSSIONS AND FUTURE WORK

This research demonstrates the value of visual methods in examining echo chambers in online political discussions, though several limitations exist. The use of predefined clustering techniques and network construction methods may influence the detected structures, potentially missing alternative patterns of ideological alignment.

Methodological Implications and Limitations. There are potential biases in network construction and clustering parameters. The reliance on Pantip data limits the generalizability of the findings, highlighting the need for future research to validate these methods across diverse platforms. Scalability and interpretability remain key challenges, as large networks can lead to visual clutter, and community detection outcomes may vary depending on algorithm selection. Future studies should incorporate weighted edges to account for interaction strength and explore methodologies to enhance both scalability and interpretability.

This study does not make normative judgments on political alignment but employs visual methods to analyze structural patterns. Future research should refine the understanding of echo chamber dynamics by examining peripheral communities and the evolution of online discourse.

Expanding Visual Analysis Techniques. Future work could incorporate advanced dimensionality reduction techniques, such as UMAP, for better user clustering and high-dimensional structure preservation. Dynamic visualizations tracking changes in echo chamber intensity over time would enable researchers to observe how polarization evolves during major political events or shifts in user interactions.

Exploring Platform Influence and User Behavior. Echo chambers tend to intensify during political events due to increased engagement. Future studies should examine the influence of platform algorithms, such as recommendation systems, on exposure to diverse viewpoints. Testing algorithm changes could help reduce polarization while maintaining user engagement.

Enhancing Echo Chamber Metrics and Applications. While the visual methods provided valuable insights, developing new metrics could capture subtler aspects of echo chambers, such as exposure to contrasting opinions or content-based polarization. These metrics could be used in cross-platform studies or to evaluate interventions aimed at reducing polarization.These metrics could be applied in cross-platform studies or used to evaluate interventions aimed at reducing polarization. Real-time social media monitoring could also help identify emerging echo chambers and enable timely interventions to promote balanced discourse.

Future work should incorporate quantitative metrics, such as clustering quality, modularity, and correlation with expert classifications, to objectively assess how different methods capture echo chamber phenomena. A comparative table or performance evaluation would enhance transparency and provide clearer guidance on method selection.

7 CONCLUSION

This study developed visual methods for Network Analytics of Echo Chambers, with a specific case study on Thailand's General Election 2023. By constructing network graphs using various clustering techniques and relationship definitions, the research explored the formation and dynamics of echo chambers in political conversations. The ECS was employed to quantify polarization within online communities, revealing the influence of both method choice and political events on user behavior and discourse.

The findings highlighted the varying levels of polarization across different methods, particularly noting the stronger echo chamber effects observed under the k-means clustering method. Additionally, the research illustrated how significant political events, such as news cycles and electoral milestones, played a key role in amplifying echo chamber dynamics.

Overall, the visual methods developed in this study offer visual methods for understanding the complexities of online political discussions and the formation of echo chambers. The case study provides important insights into the impact of the 2023 general election in Thailand on online community dynamics. This work lays the foundation for future research and applications in visualizing and analyzing network-based social phenomena in the context of political communication.

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