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Social Media Users' Interactions During the Italian European Elections: A Comparative Analysis of Two Political Leaders' Followers Using a Sentiment Analysis Algorithm

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Abstract

This study aims to integrate Social Network Analysis (SNA) methodologies with text analysis to examine public sentiment surrounding Italian political figures during the 2024 European election campaign. Specifically, Instagram comments from the profiles of two political leaders were collected over a defined period, April 8th to June 7th, 2024. Subsequent text extraction was performed, followed by sentiment analysis using Feel-it. The resulting sentiment scores were then employed to construct a signed network, enabling the visualization and analysis of positive and negative interactions within the observed online discourse.

Keywords: *Textual analysis; Social network analysis; Sentiment analysis; European elections.*

1. Introduction

Social Networks have played a fundamental role during electoral campaigns for years (Jensen & Schwartz, 2022; Shmargad & Sanchez, 2022; Bright et al., 2020). Through their use, candidates influence the political debate by determining the most important issues (Arman, 2024); on the other hand, followers tend to polarise in agreement or disagreement with the position of the candidate (Belcastro et al., 2022). Some authors have highlighted the value of analysing debates and polarisation on social networks during election campaigns as a valuable tool for predicting election outcomes (Brito et al., 2021). Instagram, which is fundamentally based on images, fosters a closeness to the candidate that extends beyond the issues they present themselves (Haßler et al., 2023). From a generational perspective, furthermore, this social network is predominantly used by young people belonging to so-called Generation Z, who are more inclined towards the personalisation of politics and, therefore, more prone to polarisation (Parmelee et al., 2022). Finally, different studies have employed sentiment analysis (SA) in the specific context of analysing electoral campaigns on social networks, primarily focusing on detecting the ability of prevailing sentiment to predict electoral outcomes (Gaur & Yadav, 2025; Chauhan et al., 2021; Ceron et al., 2016). Others employed SNA and textual information to analyse online social networks' debates on diverse topics, for instance, to detect polarised communities in the vaccine debate (D'Agata et al., 2024; 2025). In this work, we analyse the online debate ahead of the Italian election for the renewal of the European Parliament held on Saturday, June 8, and Sunday, June 9, 2024, were the party that received the largest vote share (28.76%) was 'Fratelli d'Italia' ('Brothers of Italy'), led by the current Prime Minister Giorgia Meloni, followed by the 'Partito Democratico' ('Democratic Party') (24.11%). We focus on the pre-election debate comparing the comments on Instagram to posts published by Giorgia Meloni and those on the posts of Elly Schlein, leader of the Democratic Party. From a methodological perspective, following De Stefano & Santelli (2019), we propose an integrated approach combining sentiment analysis (SA) and social network analysis (SNA). In this paper, SA is conducted as the initial phase of a procedure that, through the sentiment score, enables the construction of a signed network in a second phase (Doreian & Mrvar, 2009). This procedure allows for capturing both positive and negative interactions among the nodes (users) of the network and examining the differences related to the two political leaders. Finally, the proposed approach is an innovative application that incorporates textual data, such as SA, into a network framework to reconstruct users' interactions in a nationally based political debate on an online social network platform. Combining relational and textual data analysis enables a comprehensive understanding of online political discourse and its polarisation in relation to the content published by political leaders.

2. Data and methodology

The dataset has been built by collecting the texts of comments on the posts of the leader of Brothers of Italy (a right-wing party) and Prime Minister Giorgia Meloni, as well as the leader of the Democratic Party (a center-left party) and the main opposition party leader, Elly Schlein. The extraction of comments was carried out using web scraping procedures and covered the two months preceding the elections. Specifically, the data collection began on April 12, 2024, and ended on June 7, 2024. Figure 1 shows the word clouds of Schlein (left side) and Meloni (right side). Preliminarily, it is interesting to note that Meloni's cloud shows a high frequency of her name and surname, while in Schlein's one, her name is rare. Furthermore, in Meloni's cloud, no other politician's names appear. On the other hand, Schlein's word cloud contains the names of other politicians, including Salvini, Renzi, and Meloni. This initial descriptive information suggests a stronger personalisation of Giorgia Meloni than what we observe in Schlein.

2.1. Example of Subsection

Figure 1. Word Cloud Schlein (left) and Meloni (right).

Table 1. Directed network statistics of Meloni and Schlein's networks

	Meloni	**Schlein**
Max in-degree	849	200
Max out-degree	307	226
Max in+out degree	849	301
Density	0.00011	0.000451
Reciprocity	0.183	0.206
Transitivity	0.00335	0.0130
Nodes (users)	20061	4666
Links (interactions)	45511	9810
Average degree	4.54	4.21

To map the interaction between users, we selected comments that were direct replies to other comments, capturing both the replier and the original commenter. This filtering reduced the corpus of the initial frame of interactions. From this, we selected only the 50 most frequent users to identify the most active actors. We analysed the resulting dataset using Feel-it, a BERT-based algorithm suitable for sentiment detection in the Italian language (Bianchi et. al., 2021) to label each comment with a (-) for a negative sentiment and (+) for a positive sentiment. We construct a directed graph in which a signed edge from actor A to actor B is generated if it represents A's reply to B (or vice versa), with the edge sign indicating the sentiment polarity. We applied social network analysis tools to investigate the properties and characteristics of the network by analysing the entire network's topological structure and centralisation scores.

For our study, we considered the following statistics (see Table 1):

- Nodes: number of actors involved in the network.
- Links: Number of interactions between users.
- Average Degree: the average number of connections (links) per node in the network, considering both ingoing and outgoing links.

- Maximum in-degree and out-degree, the highest number of incoming and outgoing edges for any node in the network.
- Density is a measure of how connected the network is. A density close to 0 indicates a sparse network, meaning there are relatively few connections compared to the total possible connections.
- Reciprocity measures the proportion of reciprocal connections—that is, when two users reply to each other's comments.

After this first phase, we extended the work by combining sentiment analysis and SNA and transforming these networks into signed networks, as suggested by the balance theory. This results in the extension of the theory proposed by Cartwright and Harary (1956), which builds upon Heider's (1946) concept of cognitive balance, applying it to social networks by introducing the concept of 'structural balance.' The theory analyses a network with positive and negative ties, where the balance is achieved when every closed path (cycle) has an even number of negative ties.

This means that actors can be divided into two groups, where members of each group like each other (positive ties) and members of different groups dislike each other (negative ties). The theory states that people prefer this balanced situation, and if the network is unbalanced, they tend to change their relationships to make it so. So, one of the central claims is that actors prefer such balanced structures, and they tend to remove imbalances by adapting ties.

Following this concept, we assigned a negative sign to comments that the algorithm identified as negative and a positive sign to those identified as positive.

These resulted in the following network, where nodes interact, and links are coloured based on the sentiment assigned to the comment they wrote. Fig. 2 represents the network of the 50 most active nodes.

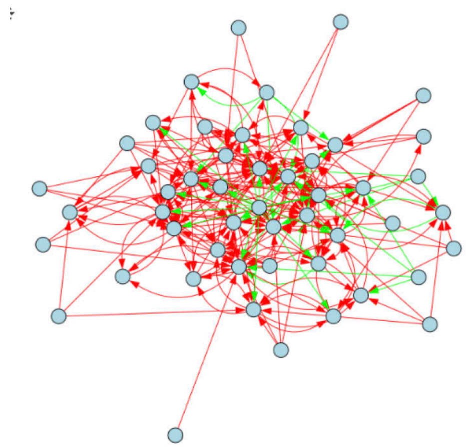

Figure 2. Most 50 active nodes of the "Schlein" network.

3. Results

In this work, we combined network analysis and the use of textual algorithms for sentiment detection. As the latter uncovers the overall emotional tone of user comments, the topological network metrics (e.g., connectivity, centralisation, and dynamics) reveal the underlying structure and interaction patterns. These metrics allow for comparison of the two networks. The "Meloni" network results in significantly larger dimensions, comprising 20,061 nodes (representing single users) and 45,511 directed links (indicating signed interactions among users, specifically responses to comments), compared to the "Schlein" network, which consists of 4,666 nodes and 9,810 links. One of the fundamental metrics of network connectivity is the degree distribution, which describes the distribution of links among nodes. The "Meloni" network has a maximum in-degree of 849, indicating that a single node receives up to 849 incoming comments, whereas the "Schlein" network's maximum in-degree is significantly lower at 200. Similarly, the maximum out-degree is 307 in the "Meloni" network compared to 226 in the "Schlein" network. The maximum combined in-degree and out-degree follows a similar trend, with "Meloni" reaching 849 and "Schlein" peaking at 301. These values suggest that the "Meloni" network contains more influential hubs that accumulate a higher number of connections, potentially signifying a more centralised structure. This could also be translated as the presence of highly connected hubs that could play a crucial role in information dissemination or control within the network.

Network density, which measures the extent to which nodes are interconnected relative to the total possible connections, is higher in the "Schlein" network (0.00045) than in the "Meloni" network (0.00011). This suggests that while the "Meloni" network is larger, its nodes are less densely connected. Reciprocity, measured as the proportion of bidirectional links in a directed network, is slightly higher in the "Schlein" network (0.206) compared to the "Meloni" network (0.183), indicating a marginally greater tendency for mutual interactions. Additionally, transitivity, a global measure of triadic closure, is 0.00335 for "Meloni" and 0.0130 for "Schlein." The higher transitivity in "Schlein" indicates a more pronounced global tendency toward forming closed triangles, potentially signifying tighter local structures. Overall, the network structure suggests that the "Meloni" network result is larger and exhibits a higher presence of hubs. On the other hand, the network of Schlein is much denser, with a higher tendency for mutual interactions (i.e., larger reciprocity).

Finally, analysing the number of links present in the Schlein network, we obtained 2,152 positive links and 6,647 negative links, indicating a strong imbalance between positive and negative links, with 2,152 positive connections compared to 6,647 negative ones. This suggests a network characterised by a prevalence of negative interactions, which could indicate conflict dynamics, polarisation, or competition among nodes.

4. Future Work

Based on the initial findings of this research, we intend to extend the study in several directions. The first of these will involve implementing dynamic network models, specifically the application of Relational Event Models (Butts et al., 2023). The second phase of our work will focus on applying a clustering algorithm to a signed network to identify groups that are organised around specific topics. The latter aims to improve sentiment analysis by allowing a better assignment of polarity, taking into account context and hidden meanings that the algorithm may not be able to detect. This would require the use of trained Large Language Models that takes into account the context of the interaction to detect more accurate shades. Further exploration of node centralities, path lengths, and modular structures could provide deeper insights into this network's underlying dynamics. A limitation of this paper is the reliance on an algorithm that uses a fixed dictionary. Finally, given the network of other political leaders, we could expand the analysis and deepen the distribution of the signed links.

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