Envisioning the Future of Communication

Vol 2, No 1 (2025)

Envisioning the Future of Communication - Conference Proceedings vol. 2

Sentiment Analysis in the Political Dialogue

Valia Kaimaki, Aggeliki Sgora, Dimitris Ampeliotis

doi: [10.12681/efoc.7920](https://doi.org/10.12681/efoc.7920)

Sentiment Analysis in the Political Dialogue: Case Study of the Candidates for the Presidency of the SYRIZA-Progressive Alliance party

Valia Kaimaki, Aggeliki Sgora, Dimitris Ampeliotis *

Abstract

Sentiment analysis can offer valuable insights into the overall mood and emotional tone of a political discussion. Building upon a prior study conducted by the iMEdD (Incubator for Media Education and Development), which examined sentiments in political communication during the 2023 elections, our current study focuses on analyzing speeches delivered by the five candidates for the presidency of the party at the Continuous Congress of Syriza – Progressive Alliance on September 2nd, 2023. Through sentiment analysis, our objective is to determine whether the apparent positive tone in candidates' speeches reliably predicts electoral success and whether the topics addressed in each speech influence its overall sentiment. Our findings indicate that positive sentiment in political speeches does not necessarily correlate with electoral victory and that certain topics positively influence overall sentiment.

Keywords: sentiment analysis, political communication, elections, Syriza – Progressive Alliance.

Introduction

One approach to conducting political analysis is through sentiment mining. Generally, sentiment mining involves a range of techniques designed to extract and analyze positive and negative feelings, opinions, attitudes, or emotions (Liu 2012). The field of sentiment analysis has been developing for nearly two decades. This area of study focuses on detecting and categorizing the subjective elements of language, particularly the expression of positive or negative feelings (Shanahan, Qu, & Wiebe 2006). Initially, sentiment analysis utilized a range of linguistic tools including comprehensivethesauri, lemmatizers, etc to determine the presence and nature of sentiment in texts. Over time, however, the field has shifted towards more automated techniques.

Sentiment analysis involves a detailed exploration of emotions, opinions, evaluations, and attitudes related to various subjects such as "services, products, individuals, organizations, issues, topics, events and their attributes" (D'Andrea et al. 2015: 27). These elements are inherently subjective and typically align with polarities such as positive/negative, good/bad, and pro/con, although

* Valia Kaimaki, Assistant Professor, Department of Digital Media and Communication, Ionian University.
Aggeliki Sgora, Assistant Professor, Department of Digital Media and Communication, Ionian University.
Dimitris Ampeliotis, Assistant Professor, Department of Digital Media and Communication, Ionian University.

options for neutrality or no opinion are also present. Consequently, sentiment analysis seeks to "extract subjectivity and polarity" in language to ascertain the "semantic orientation" or "the polarity and strength of words, phrases, or texts" (Taboada et al. 2011: 268). This type of analysis offers critical insights for diverse sectors, including business, where it impacts product and service perceptions, as well as in political and sociological contexts, addressing public issues and policies (Feldman 2013). In political arenas, extensive research has utilized X (former) Twitter data to assess public sentiment towards po litical figures, issues, and the predictive utility of these sentiments (e.g., Murthy 2015). Beyond X, where public opinions are expressed, there is another fertile area for research, namely the political rhetoric during elections. Scholars have initiated investigations into the narratives of Hillary Clinton, Donald Trump, and other contenders in the 2016 US presidential race (Degani 2016, Liu & Lei 2018), as well as drawing comparisons with other political leaders (Dilai, Onukevych & Dilay 2018).

Regarding methodologies for sentiment analysis, two predominant techniques exist: machine-learning and lexicon-based approaches, with the possibility of utilizing a hybrid approach that merges these strategies (D'Andrea et al. 2015). The recent, groundbreaking success of the so-called deep-learning methods has revolutionized many domains including sentiment analysis (Young et al. 2018). Sentiment analysis is a fundamental aspect of natural language processing (NLP), focusing on the automated classification or scaling of documents by their overall polarity on a continuum from positive to negative (Küçük & Can 2020; Pang, Lee, and Vaithyanathan 2002). On the other hand, the lexicon-based method employs a sentiment lexicon, which includes words associated with specific sentiments, to evaluate the sentiment within a given text.

The machine-learning and lexicon-based approaches to sentiment analysis each display distinct advantages and challenges. The machine-learning method is lauded for its "ability to adapt and create trained models for specific purposes and contexts," (D'Andre a et al. 2015: 29) yet it faces limitations in terms of applicability due to the scarcity of readily available labeled data, particularly across diverse domains such as business and politics. Conversely, the lexicon- based approach is favored for its "wide term coverage" (Taboada et al. 2011) and is often preferred when the machine-learning approach proves less feasible across different fields. Existing tools and lexicons, such as those developed by Jockers(1) and Tausczik and Pennebaker (2010), demonstrate effectiveness and utility across various domains.

It is crucial to recognize that sentiment analysis can be conducted at three distinct levels: document-level, sentence-level, and aspect-level (Lv et al. 2021). Document-level analysis is focused on gauging the overall sentiment of an entire document, operating under the assumption that the document expresses a principal opinion about a specific entity or topic (Behdenna 2016). In contrast, sentence-level analysis delves into the sentiment expressed within individual sentences, thereby offering more granular insights compared to document- level analysis. Aspect-level analysis, on the other hand, is particularly pertinent for entities that have many aspects (attributes), such as consumer products. Consequently, aspect-level analysis is extensively utilized for evaluating consumer products.

The advent of ChatGPT and similar large language models have significantly enhanced the accessibility of machine learning methodologies, particularly for those without any programming knowledge. This development is proving transformative for researchers in the social sciences and opens numerous new avenues for exploration. Originally employed to assess public sentiments towards politics, sentiment analysis has now expanded to include studies focused on political speeches using machine learning tools (Van Atteveldt, Kleinnijenhuis et al. 2008; Burscher et al. 2014; Ceron et al., 2015). These studies have shown promising results in measuring sentiment at the level of articles or speeches (Hopkins & King 2010). The emerging question is how platforms like ChatGPT can further simplify the sentiment analysis process, making it even more user-friendly and widely applicable.

To this end the iMEdD (Incubator for Media Education and Development) -a non-profit journalism organization established in 2018 with funding from a grant provided by the Stavros Niarchos Foundation (SNF)- conducted in 2023 a comprehensive study (Troboukis & Kiki 2023) analyzing the campaign speeches of political leaders from the six parties represented in the Greek parliament during the 18th Parliamentary Term, which spanned from July 17th, 2019, to April 22nd, 2023. This study included speeches from the May and June 2023 elections. Its aim was to identify the main themes addressed by political leaders, determine which topics were emphasized most, and explore the qualitative characteristics of their political discourse.

To address these questions, iMEdD employed a mixed-method approach that combined human expertise and artificial intelligence. The integration of the advanced ChatGPT interactive model, a standout in AI innovation, enhanced their analytical process. This model's capabilities allowed them to delve deeper into the intricacies of political rhetoric and its impact. The project served as an experimental collaboration among professionals in journalism, political theory, and data science, alongside AI, with twin objectives: to dissect the content of campaign speeches and to test the limits of modern technology.

One particularly interesting finding emerged from the study: Kyriakos Mitsotakis, the leader of the conservative New Democracy party and the victor of both elections, consistently displayed a positive sentiment throughout his speeches. This observation led to the formulation of the following new research questions:

1. What topics are discussed in the candidates' speeches?

2. Does a positive emotional tone in speeches correlate with electoral success? The field of election forecasting through sentiment analysis is rapidly expanding. It leverages natural language

processing and machine learning to predict political election outcomes by examining the sentiments expressed in online discussions and news articles (Alvi et al. 2023). Could the sentiment also predict the outcome of elections?

3. Is averaging paragraph sentiments the most effective method for gauging emotional content in the whole speech? The iMEdD study uses just the average of each paragraph to calculate sentiments in the whole speech.

4. Are there more reliable indicators than emotional tone for predicting electoral outcomes?

5. To what extent do the themes of a speech influence its overall sentiment?

More specifically, in this paper we seek to answer these research questions by analyzing the speeches delivered by the five candidates for the presidency of the party at the Continuous Congress of Syriza – Progressive Alliance on September 2nd, 2023.

The political context

After the general election in June 2023 in Greece, Alexis Tsipras, the leader of the left party Syriza - Progressive Alliance, resigned. His trajectory began in February 2008 when he was elected as the head of the Coalition of the Left, which later became known as Syriza. At that time, the party had a mere 5.04% of the vote. Under the leadership of Alexis Tsipras, the party not only increased its vote share but also became the major partner in a coalition government from 2015 to 2019. Although the party and Tsipras himself were accused of failing to fulfill their electoral promises, particularly regarding the respect of the memoranda signed with the Troika (International Monetary Fund, European Central Bank, and European Commission) to bail out the country f rom its debt, the government met all its obligations to the Troika and managed to usher in a new chapter for the country. The party lost the 2019 election but still garnered a relatively high 31.53% of the vote, only 4 percentage points down from 2015. Nevertheless, in May 2023, the party barely managed to achieve over 20% (20.07%), and in the June election, it failed to recover, securing only 17.83%.

The numbers were relentless and solely sufficient to compel Alexis Tsipras to step down. He announced his resignation four days after the elections, on June 29, 2023. He stated that the party needed "profound renewal and refoundation" (Stamouli, 2023). This opened the race for succession, which concluded in September of the same year when party members were called to select a new leader through direct elections. The climax of the "pre-election campaign" for the five candidates was at the SYRIZA - Progressive Alliance's Permanent Conference held on Saturday, September 2, 2023, featuring only the five candidates as speakers.

For research purposes, we provide some information about each candidate. Ms. Effie Achtsioglou, until the eve of the election, was the leading candidate. A doctor of law and a former minister in SYRIZA-PA governments, she was unblemished at the party level, young, dynamic, leftist, but also a technocrat. Euclid Tsakalotos, former Minister of Finance, and professor of economics was the person who concluded the memoranda and began refilling the country's coffers. He represented the party's most left-wing faction. Nikos Pappas, the right- hand man of the former prime minister and president of SYRIZA-PA, Alexis Tsipras, also an economist, attracted the opposition's criticism due to the controversial law regulating private television stations. Stefanos Tzoumakas, coming from PASOK, the once dominant socialist party, had served as minister in various capacities in its governments. Stefanos Kasselakis, a businessman who made his fortune in the US, was the "outsider" of the election. Without previous ties to the party or the left, he had been selected by Mr. Tsipras as the representative of the Diaspora on the party's state list ballot. Despite Effie Achtsioglou being the favored candidate, Stefanos Kasselakis prevailed in both rounds. The order of the candidates was: First Round - Kasselakis 44.91%, Achtsioglou 36.18%, Tsakalotos 8.93%, Pappas 8.68%, Tzoumakas 1.3%. Second Round: Kasselakis 55.98%, Achtsioglou 44.02%.

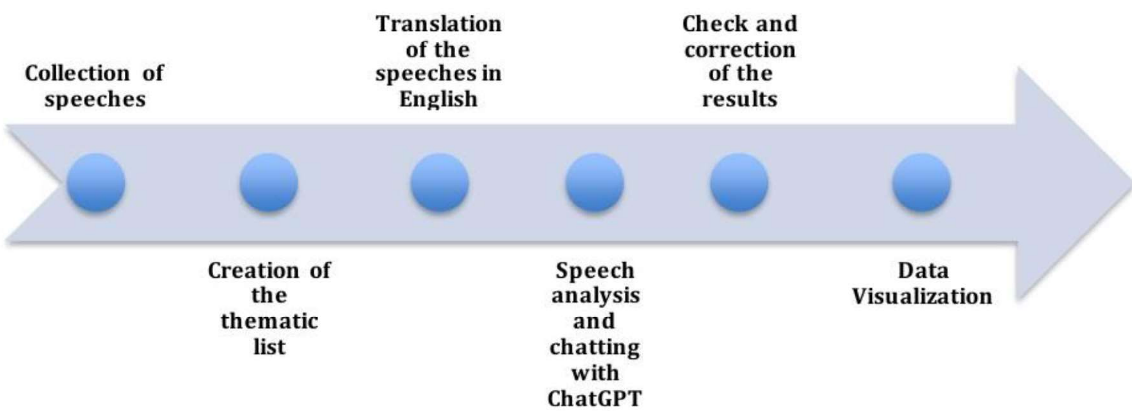

Figure 1: Our methodology

Methodology

To address the research questions, as already mentioned, we adopted and expanded upon the methodology used in the iMEdD study, supplemented by findings from related research (Troboukis & Kiki 2023). Our approach, as illustrated in Figure 1, comprises the following steps:

Step 1: Collection of speeches

Our analysis focused on the speeches given by the five candidates at the Continuous Congress of Syriza – Progressive Alliance on September 2nd, 2023. We acquired the complete transcripts of these speeches through the Press Relations department of the party. This primary source material ensured the accuracy and comprehensiveness of our data, allowing for a detailed examination of the rhetorical and thematic elements present in the political discourse of the candidates.

Step 2: Creation of the thematic list

For Step 2 of our analysis process, we developed a list of thematic areas commonly found in political speeches. While we took into account the thematic categories provided in the iMEdD study (Troboukis & Kiki 2023), our list has been expanded to reflect specific aspects relevant to the electoral context. For example, terms like "left" have been included to capture ideological leanings pertinent to the speeches under review. The enriched list of thematic elements includes:

• Accountability	• Agricultural policy	• Civil protection
• Corruption	• Culture	• Debt
• Democracy	• Economy	• Education
• Elections	• Employment	• Energy
• Entrepreneurship	• Environment	• Europe
• External affairs	• Health	• Housing
• Human rights	• Infrastructure	• Justice
• Left	• Media	• Migration
• National security	• Pandemic	• Pensioners

• Privatization	• Public sector	• Social state
• Tourism	• Transparency	• Other

The element other is used to categorize paragraphs that do not fit any of these thematic areas.

Step 3. Translation of the speeches in English

During this phase, the formatted text was translated into English using DeepL Translator (https://www.deepl.com/). DeepL employs machine learning technology, specifically Convolutional Neural Networks (CNNs), to provide precise translations. This technology is adept at capturing the nuances and specific terminology of the original speeches, which is essential for conducting a detailed and accurate analysis. Translating the content into English ensures that the analysis can leverage the capabilities of ChatGPT, which has a more extensive vocabulary and better understanding in English. This step is vital for preserving the integrity of the political discourse analysis, enabling more nuanced insights and interpretations.

Step 4. Speech analysis and chatting with ChatGPT

The analysis of political leaders' campaign speeches will primarily occur at the document level; however, for greater precision, it will initially be conducted at the paragraph level. After evaluating individual paragraphs, an averaging process will aggregate these findings to provide an overall assessment. The analysis will focus on the following aspects:

• Main Topic Identification: Each paragraph is analyzed to determine its main topic, based on the predefined list of topics above. This list helps categorize and understand the focal points of each speech segment.

• Sentiment Analysis: The dominant sentiment expressed in each paragraph is identified and categorized as positive, neutral, or negative. By analyzing sentiment at the paragraph level, we can gain a nuanced understanding of how the speaker's tone varies th roughout the speech and how it aligns with different thematic elements.

Using the ChatGPT API (gpt-3.5), we engage in a programmatic chat with the interactive AI model to analyze the campaign speeches. Specifically, we prompt ChatGPT to provide us with several linguistic features for each paragraph of the campaign speeches, including:

Topic/Theme Identification: The AI is prompted to determine the most likely topic or theme discussed in each paragraph of the political speech. This approach helps categorize content systematically, ensuring that thematic analysis aligns with predefined categories.

Sentiment Analysis: ChatGPT evaluates the sentiment of the speech paragraph, providing a sentiment value on a scale from -1 to 1. A value equal to +1 represents a paragraph that evokes the highest positive sentiment, whereas a value equal to −1 represents a paragraph that, according to the language model, evokes the most negative sentiment. Moreover, we also consider a "rounded" version of the sentiment coefficient as Table 1 presents. The corresponding intervals have been obtained by dividing the interval [-1, 1] into three sub- interval of equal length. The classification is divided into three categories:

a) Negative: If the score ranges from -1 to -0.34, indicating a predominantly negative sentiment.

b) Neutral: If the score falls between -0.33 and 0.33, suggesting a balanced or indifferent emotional expression.

c) Positive: If the score lies between 0.34 and 1, reflecting a primarily positive sentiment.

Table 1: Classification of the dominant sentiment according to the value of the sentiment coefficient X

X value	$x \in [-1, -0.34]$	$x \in [-0.33, 0.33]$	$x \in [0.34,1]$
Result	Negative	Neutral	Positive

Such quantification allows for precise measurement of emotional tone across different parts of the speech, contributing to a deeper understanding of how sentiments are distributed throughout the speech and their potential impact on the audience.

Step 5: Check and correction of the results

For each speech being analyzed, we construct a dataset consisting of rows corresponding to the number of paragraphs in the speech and columns representing the variables being studied. Following this, in step 5 we review and refine the results obtained from ChatGPT.

Each paragraph under analysis is reviewed by the researchers who assess the ChatGPT outputs based on the main topic of discussion. Should the ChatGPT results prove inaccurate, the working group steps in to make the necessary adjustments. Paragraphs that touch upon multiple issues are categorized based on the most dominant topic discussed. This method ensures clarity and precision in understanding the primary focus of each speech segment.

On the contrary, if ChatGPT assigns a sentiment score that categorizes a paragraph differently from human judgment, the misclassified value is removed from the dataset and excluded from further analysis or visualizations. The researchers have followed the same method as iMEdD (Troboukis & Kiki, 2023) who chose deletion as the method to correct such discrepancies, as it is deemed the most effective strategy to maintain the integrity of the average sentiment indicators. This approach prevents ad hoc human adjustments that could skew the overall classification of the election speech as negative, neutral, or positive. This procedure ensures that the analysis remains consistent and unbiased, providing a clear and accurate representation of the sentiment conveyed in the speeches.

In our study the percentage of the successful categorization of the sentiments on behalf of chat GPT was 83%, according to the manual consequent categorization. So the researchers excluded 17% of chat GPT's automatic sentiment results.

Step 6: Data visualization

During the last step several tools are used is order in order to visualize the obtained results. More specifically, the free online generator wordclouds (worldclouds.com) is used in order to visualize the main topic of the paragraphs of the speeches. Also, we utilize MS ExcellTM to generate the diagrams that demonstrate the sentiment coefficient as a function of time, and the so-called Radar charts that show the numbers of positive, neutral, and negative paragraphs of each speech.

Results regarding the primary topics of the speeches

In this section, we illustrate the primary topics discussed in the candidates' speeches. More specifically, as depicted in Figure 2, Democracy and Economy emerged as the two most frequently discussed topics, showing a significant difference from the other topics. One interesting point from the analysis is that only 20 topics out of the 33 of the lists.

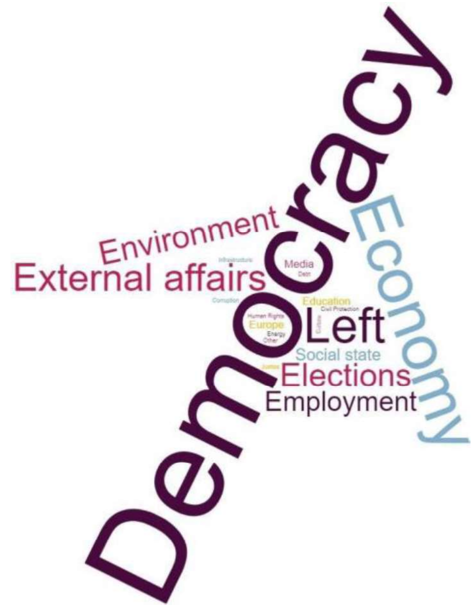

Figure 2: Topics discussed in candidates'

In Ms. Achtsioglou's speech, as figure 3 depicts, only 9 topics are discussed, with Democracy and Economy being the two most frequently addressed. Additionally, she focuses solely on issues related to the social state, and justice.

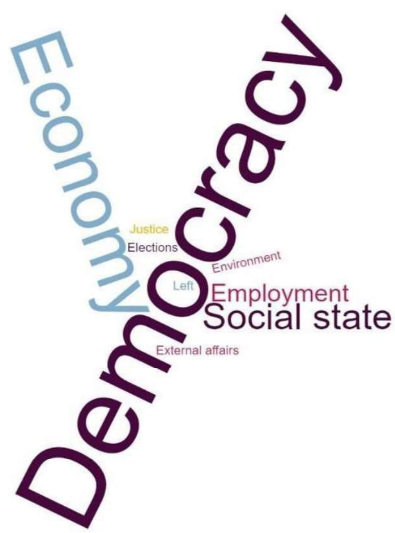

Figure 3: Topics discussed in Ms. Achtsioglou's speech.

In Mr Kasselakis' speech, as figure 3 depicts, also only 9 topics are discussed, with Democracy and Economy being the two most frequently addressed. Furthermore, the frequency of these topics is comparable to that of the other 7 topics. Additionally, he focuses solely on issues regarding media, culture, debt, and corruption.

Figure 4: Topics discussed in Mr. Kasselakis's speech.

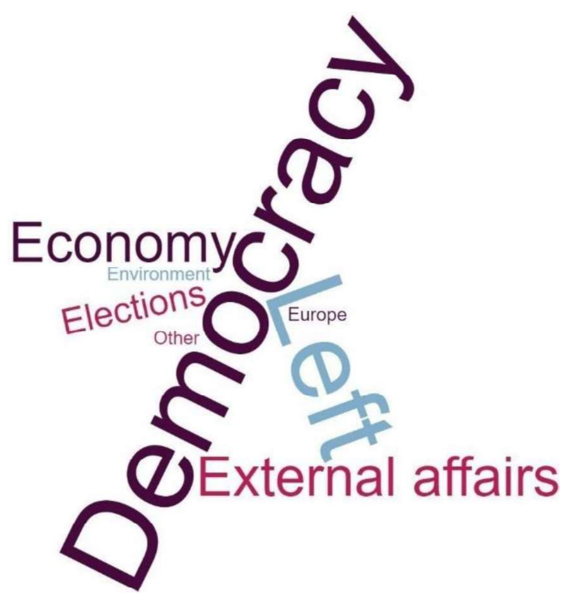

Figure 5: Topics discussed in Mr. Pappas's speech.

In Mr. Pappas's speech, as figure 5 depicts, only 8 topics are discussed, with Democracy, Economy and Left being the two most frequently addressed. Additionally, an interesting observation is that there is a paragraph in his speech that cannot be classified within the list of topics.

Figure 6: Topics discussed in Mr. Tzoumakas's speech.

In Mr. Tzoumakas's speech, as figure 6 depicts, 11 different topics are discussed with Economy and Democracy being the three most frequently addressed. He focuses solely on issues regarding infrastructure, civil protection, and energy.

Figure 7: Topics discussed in Mr. Tsakalotos's speech.

In Mr. Tsakalotos's speech, as figure 7 depicts, only 7 topics are discussed, with Democracy and Economy and Left being the two most frequently addressed. Additionally, he focuses solely on issues related to human rights.

Results regarding the sentiment

In this section, we present the findings concerning the sentiment of the five speeches. More specifically, we illustrate the sentiment coefficient for each speech as a function of time, or more accurately, as a function of the paragraph index. Also, for each speech, we provide the so-called "Radar chart" that is computed using the counts for positive, neutral, and negative paragraphs. Furthermore, we include a Radar chart that shows the results for all five speeches in the same axes, to facilitate the comparison of the speeches with respect to the evoked sentiment.

The speech of Ms. Achtsioglou

The speech of Ms. Achtsioglou consists of 31 paragraphs. The sentiment coefficient as a function of the paragraph index is demonstrated in Figure 8. It is evident from the figure that the speech evokes mainly positive sentiment, with a rather positive conclusion. Out of the 31 paragraphs, 20 paragraphs were classified as positive, 7 paragraphs were classified as negative, and 4 paragraphs were classified as neutral. The respective Radar chart is given in Figure 9.

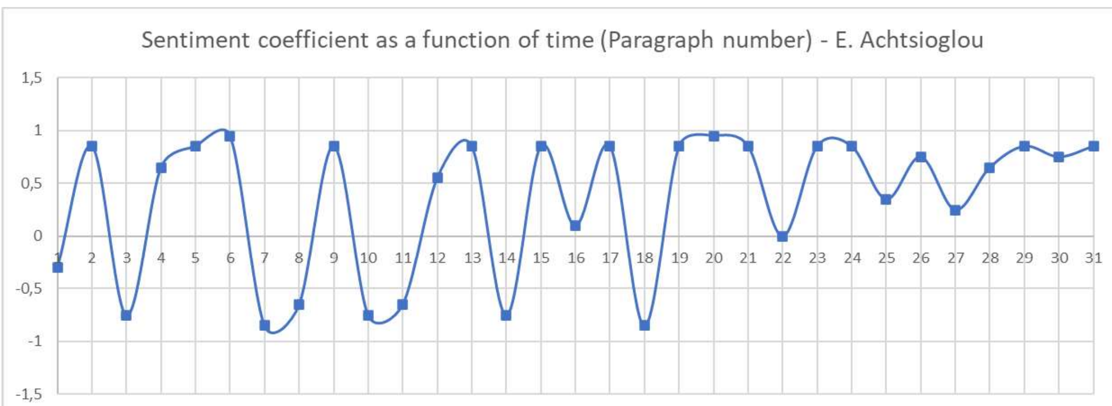

Figure 8: The sentiment coefficient for the speech of Ms. Achtsioglou as a function of the paragraph index

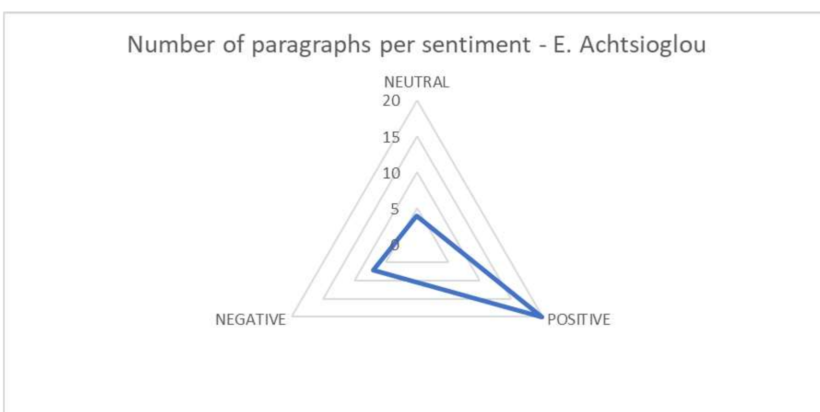

Figure 9: The Radar chart for the speech of Ms. Achtsioglou

The speech of Mr. Kasselakis

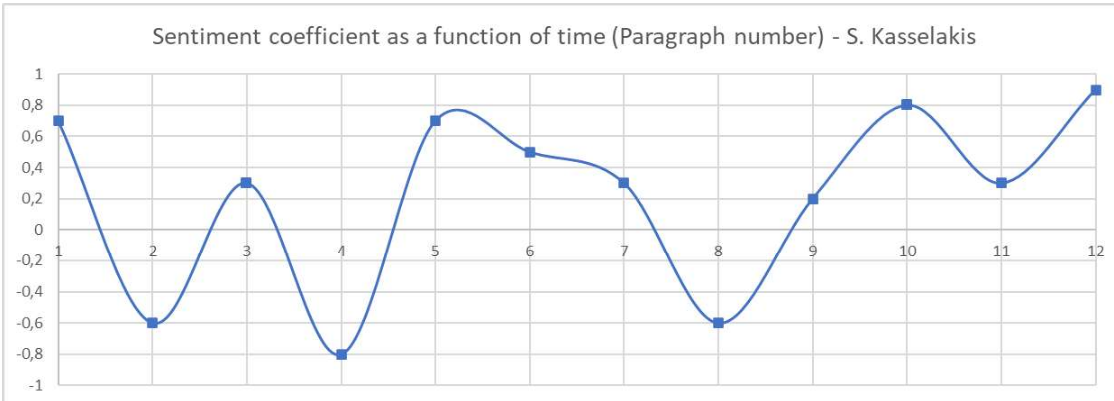

Figure 11: The sentiment coefficient for the speech of Mr. Kasselakis as a function of the paragraph index

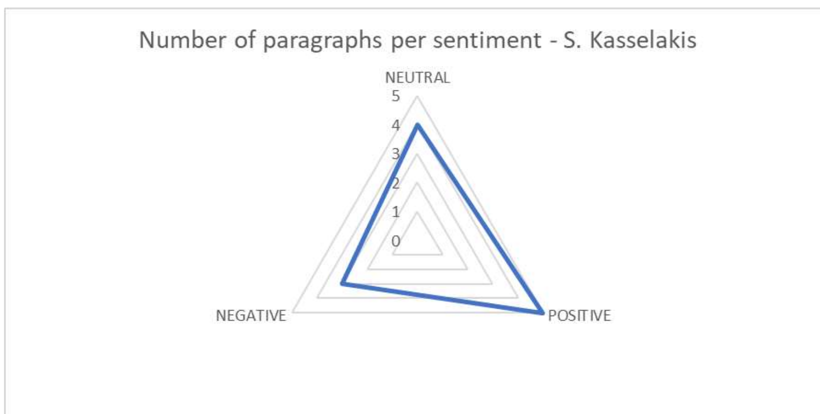

Figure 12: The Radar chart for the speech of Mr Kasselakis

The speech of Mr. Kasselakis consists of 12 paragraphs. The sentiment coefficient as a function of the paragraph index is demonstrated in Figure 10. It can be seen that the speech appears rather balanced, in the sense that the number of positive paragraphs is only slightly greater than the number of negative paragraphs. Also, the speech contains almost the same number of paragraphs that were classified as neutral. As it was also the case in the previous speech, the speaker decided to end their speech in a positive sentiment. The Radar chart for the speech of Mr. Kasselakis is given in Figure 11. Finally, a distinctive feature of the speech of Mr. Kasselakis is the fact that it contains the smallest number of paragraphs.

The speech of Mr. Pappas

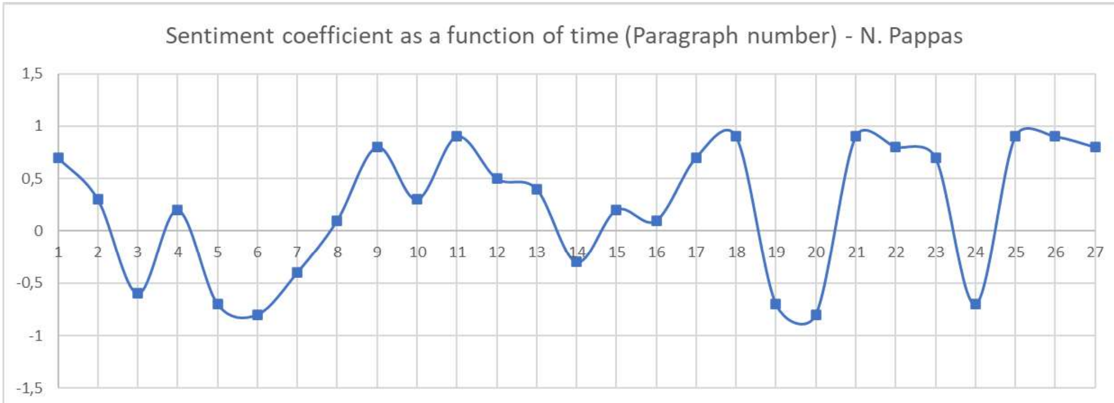

Figure 13: The sentiment coefficient for the speech of Mr. Pappas as a function of the paragraph index

The speech of Mr. Pappas consists of 27 paragraphs, 13 of which were classified as positive. The sentiment coefficient as a function of the paragraph index is demonstrated in Figure 12. The speech has an overall positive sentiment, especially in the second half and close to its end. This can be seen clearly in the Radar chart which is given in Figure 13.

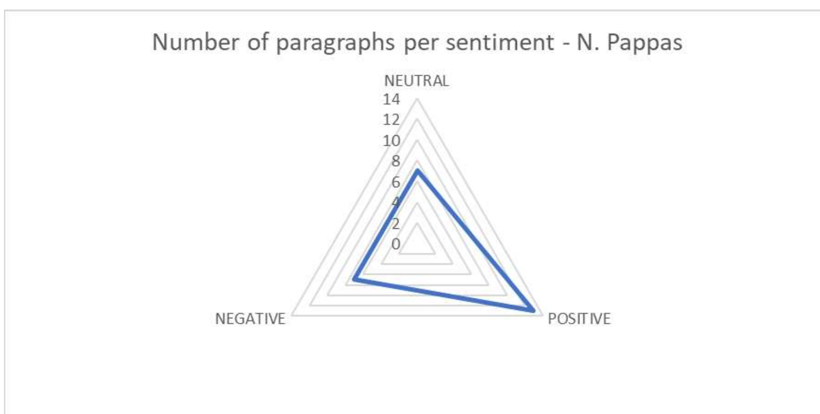

Figure 14: The Radar chart for the speech of Mr Pappas

The speech of Mr. Tzoumakas

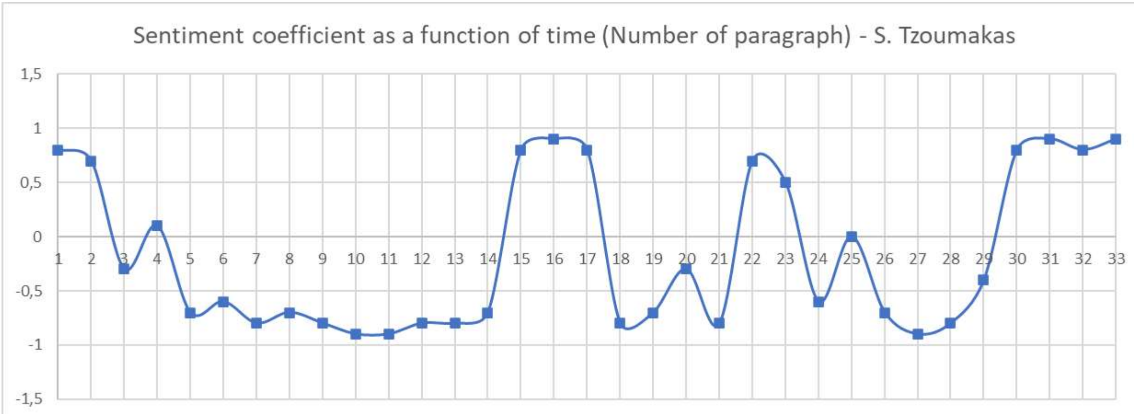

Figure 15: The sentiment coefficient for the speech of Mr. Tzoumakas as a function of the paragraph index

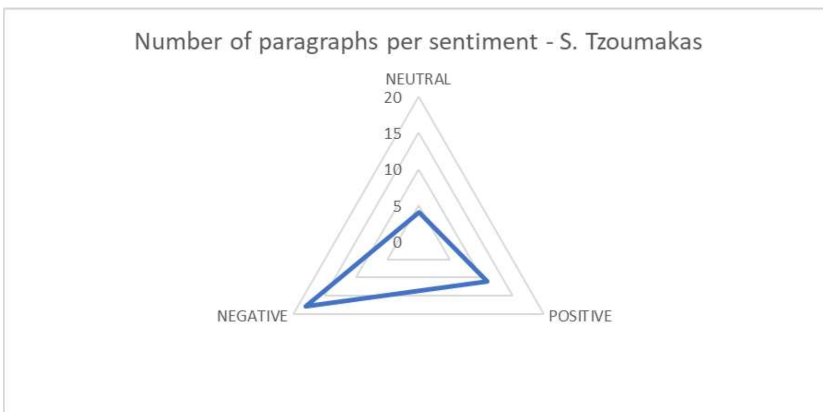

Figure 16: The Radar chart for the speech of Mr. Tzoumakas

The speech of Mr. Tzoumakas consists of 33 paragraphs, 18 of which were classified as negative. The sentiment coefficient as a function of the paragraph index is demonstrated in Figure 14. Although the speech evokes mainly negative sentiment, the speaker does choose to end in a positive way. The Radar chart for the speech of Mr. Tzoumakas is given in Figure 15, where it is evident that the speaker has focused on issues that had negative sentiment.

The speech of Mr. Tsakalotos

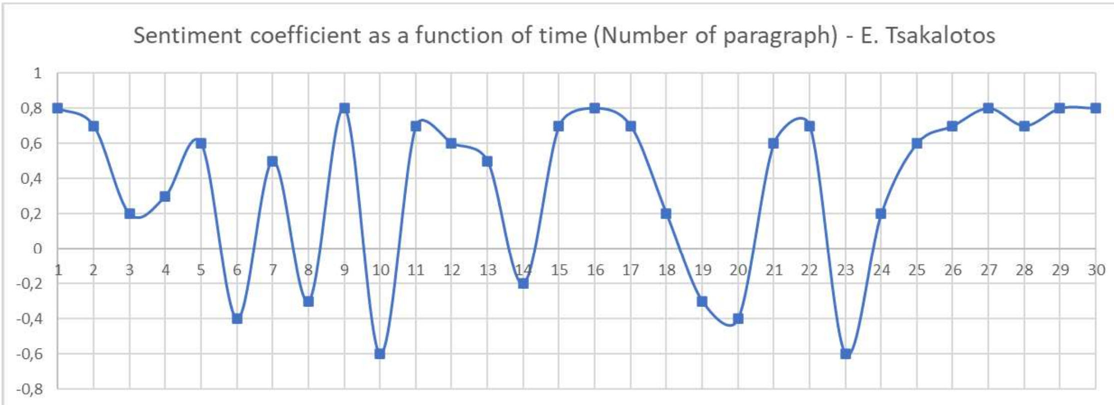

Figure 17: The sentiment coefficient for the speech of Mr. Tsakalotos as a function of the paragraph index

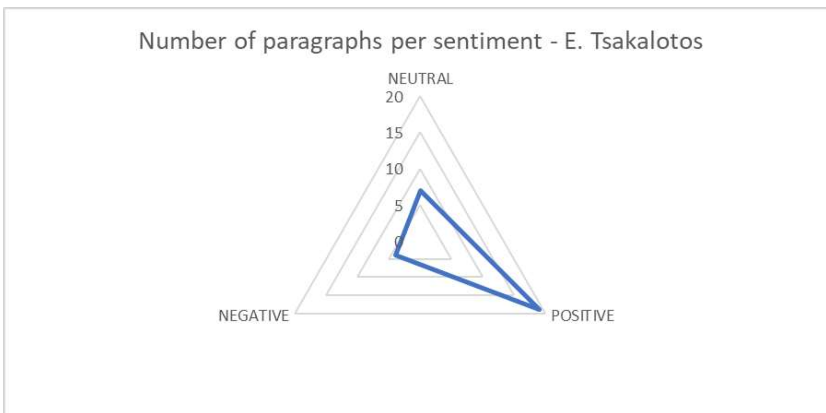

Figure 18: The Radar chart for the speech of Mr. Tsakalotos

The speech of Mr. Tsakalotos consists of 30 paragraphs, 19 of which were classified as positive. The sentiment coefficient as a function of the paragraph index is demonstrated in Figure 16. It is evident from the figure that the speech focused on positive issues. Interestingly, the smallest value of the sentiment coefficient for the speech of Mr. Tsakalotos is approximately equal to -0.6, which is the greater minimum value for all the five speeches. The Radar chart for the speech of Mr. Tsakalotos is given in Figure 17, where it can easily be seen that the speech focused on positive issues.

A comparison of the sentiment in the five speeches

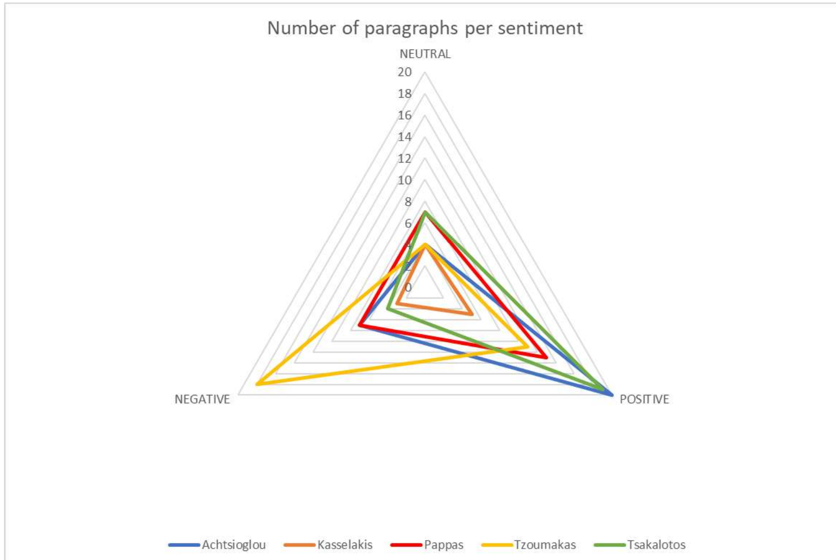

Figure 19: Radar chart for all speeches

To facilitate a comparison of the five speeches considered in this study, Figure 18 gives the Radar chart for all speeches on a shared axis. Observing this figure, it becomes apparent that all speeches except Mr. Tzoumakas's exhibit a predominantly positive sentiment. Conversely, both the speeches of Ms. Achtsioglou and Mr. Tsakalotos display a strong positive sentiment. The speeches of Mr. Pappas and Mr. Kasselakis are more balanced in terms of sentiment. Also, these speeches feature a lower number of paragraphs.

Results regarding the sentiment in conjunction with the topics

In this section, we investigate if there are certain topics in speeches that positively influence overall sentiment. In Table 2 the green color indicates a positive sentiment, the orange color a neutral sentiment, while red color indicates a negative sentiment.

As it can be seen from the analysis in Table 2 there are some topics that appear to have in all the speeches when they referred positive influence e.g. left, while other topics, e.g. economy can have positive, neutral or even negative influence. An interesting observation also is that the topics covered in the speeches of Ms. Achtsioglou and Mr. Tsakalotos are quite similar.

Table 2: Topics and Sentiment Analysis

Candidate	Achtsioglou	Kasselakis	Pappas	Tzoumakas	Tsakalotos	Overall

Economy						
Democracy						
Social state						
Environment						
Employment						
External affairs						
Elections						
Left						
Justice						
Corruption						
Education						
Debt						
Media						
Culture						
Other						
Europe						
Infrastructure						
Civil Protection						
Energy						
Human Rights						

Legend for Table 2		
Color	Sentiment	Characteristic Quote
Green	Positive	**Achtsioglou:** We are proud of our journey. **Kasselakis:** The day after my election to the party we love and for which we are working, Syriza of the Modern Left will begin. **Pappas:** During our administration we have had a strong proactive foreign policy that has strengthened the country and improved the conditions of calm in the region. **Tzoumakas:** The new generation, both for the prosperity of the country as a whole and for its individual progress and development, needs to work in the knowledge economy. **Tsakalotos**: And our identity has values, and ideas, and analyses.
Yellow	Neutral	**Achtsioglou:** A state that will finally make the necessary modernisation changes. **Kasselakis**: I have not known Syriza since I was born. **Pappas**: Today, progressive reform of the EU is more necessary than ever. **Tzoumakas**: The EU must become a state entity like the USA. **Tsakalotos**: Because we can't tell everybody everything.
Red	Negative	**Achtsioglou**: We are here today under the weight of a major electoral defeat. **Kasselakis**: We have before us a rotten state and a right-wing parastate. **Pappas**: .The transformation step was cowardly and half-hearted **Tzoumakas**: The responsibility for forest firefighting belongs to the competent body of the State, the Fire Brigade, which today, under the responsibility of the Government, has been depleted with 3,600 vacancies. **Tsakalotos**: They do not invest in new technologies, new products, new markets. They invest on the low wage.

Discussion and Conclusions

In this paper, we examine the speeches given by the five candidates vying for the party's presidency during the Continuous Congress of Syriza – Progressive Alliance on September 2nd, 2023 to determine the apparent positive tone in candidates' speeches reliably predicts electoral success and whether the topics addressed in each speech in fluence its overall sentiment. From our analysis we have identified the primary topics discussed in the candidates' speeches, with the topics Democracy and Economy addressed in all the candidates' speeches.

It is important to note that when we conducted our research in late 2023, ChatGPT had been operational for only a year, and its accuracy in the Greek language was not as high as it is now. Consequently, we had to implement step 3, which may have resulted in the loss of some language nuances, despite the researchers manually validating the translations. With the advent of ChatGPT-4, this step is no longer necessary.

From the elections' outcome it is apparent that the presence of positivity in political speeches doesn't always align with winning elections. The reason for this might be that although important, the corpus examined was not big enough so as to establish a rationale of connection/correlation between either positive or negative sentiments and winning or losing an election.. In the future, an examination of multiple speeches would allow for a statistical elaboration of the relationship between the subjects mentioned and the sentiments. Furthermore, it would be interesting to examine whether the negative sentiment is a deterrent factor for victory.

In addition, given the election outcome, it seems that the averaging of the paragraph sentiments is not the most effective method for gauging emotional content in the whole speech, since it does not capture the moments in time and in particular the outbursts that are likely to mobilize the audience emotionally and therefore politically. The sentiment coefficient for each speech as a function of time is likely to give better results but more research is needed.

Finally, the themes of a speech may likely influenceits overall sentiment, however since in this case the framework is particularly important, and we cannot look forward to generalizations.

References

Aaldering, L., & Vliegenthart, R. (2016). 'Political leaders and the media. Can we measure political leadership images in newspapers using computer-assisted content analysis?' Quality and *Quantity*, 50(5): 1871–1905.

Alvi, Q., Ali, S.F., Ahmed, S.B., Khan, N.A., Javed, M., Nobanee, H. (2023) 'On the frontiers of Twitter data and sentiment analysis in election prediction: a review'. PeerJ Computer Science. 21(9). doi: 10.7717/peerj-cs.1517.

Behdenna S., Barigou F. and Belalem G. (2016). Sentiment Analysis at Document Level. In *Proceedings of Smart Trends in Information Technology and Computer Communications. EAI Endorsed Transactions on Context-aware Systems and Applications*. SmartCom vol 628: 159-168.

Burscher, B., Odijk, D., Vliegenthart, R., De Rijke, M., & De Vreese, C. H. (2014). 'Teaching the computer to code frames in news: Comparing two supervised machine learning approaches to frame analysis.' *Communication Methods and Measures*, 8(3): 190–206. doi:10.1080/19312458.2014.937527

Ceron, A., Curini, L., & Iacus, S. M. (2016). 'First-and second-level agenda setting in the twittersphere: An application to the Italian political debate.' *Journal of Information Technology and Politics*, 13(2): 159–174.

D'Andrea, A., Ferri, F., Grifoni, P., Guzzo, T. (2015). 'Approaches, tools and applications for sentiment analysis implementation.' *International Journal of Computer Applications,* 125(3): 26-33.

Degani, M. (2016). 'Endangered intellect: a case study of Clinton vs Trump campaign discourse.' *Iperstoria*, Issue 8.

Dilai, M., Onukevych, Y., Dilay, I. (2018). 'Sentiment analysis of the US and Ukrainian presidential speeches.' *Computational linguistics and intelligent systems*, Lviv Polytechnic National University, p. 60–70

Hopkins, D. J., & King, G. (2010). 'A method of automated nonparametric content analysis for social science.' *American Journal of Political Science*, 54(1): 229–247. doi:10.1111/ajps.2010.54.issue-1

Küçük, D., and Can, F. (2020). 'Stance Detection: A Survey.' *ACM Computing Surveys* 53 (1): 1–37.

Liu, B. (2012). *Sentiment Analysis and Opinion Mining*. Synthesis Lectures on HumanLanguage Technologies. Morgan & Claypool Publishers.

Liu, D., Lei, L. (2018). 'The appeal to political sentiment: An analysis of Donald

Trump's and Hillary Clinton's speech themes and discourse strategies in the 2016 US presidential election'. *Discourse, Context & Media*, 25: 143-152.

Lv, Y., Wei, F., Cao, L., Peng, S., Niu, J., Yu, S., Wang, S. (2021). 'Aspect-level sentiment analysis using context and aspect memory network.' Neurocomputing, 428: 195-205. https://doi.org/10.1016/j.neucom.2020.11.049.

Murthy, D. (2015). 'Twitter and elections: are tweets, predictive, reactive, or a form of buzz?' Information, Communication & Society, 18 (7): 816–831. http://dx.doi.org/10.1080/1369118X.2015.1006659

Pang, B., Lee, L., and Vaithyanathan, S. (2002). 'Thumbs Up? Sentiment Classification Using Machine Learning Techniques.' In *Proceedings of the 2002 Conference on Empirical Methods in Natural Language Processing* , p. 79–86. Association for Computational Linguistics. https://arxiv.org/abs/cs/0205070Feldman, R., (2013). 'Techniques and applications for sentiment analysis.' *Communications of the ACM*, 56 (4): 82-89.

Shanahan, J., Qu, Y., Wiebe, J., eds. (2006). *Computing attitude and affect in text: Theory and applications*, Dordrecht, the Netherlands: Springer.

Stamouli, N. (2023). 'Greek opposition leader Tsipras resigns as Syriza chief after election defeat'. Politico, June 29, https://www.politico.eu/article/greek- opposition-leader-tsipras-resigns-syriza-chief-after-election-defeat/

Taboada, M., Brooke, J., Tofiloski, M., Voll, K., Sted, M. (2011). 'Lexicon-based methods for sentiment analysis.' *Computational Linguistics,* 37: 267-307

Tausczik, Y. R., & Pennebaker, J. W. (2010). 'The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods.' *Journal of Language and Social Psychology*, *29*(1): 24-54. https://doi.org/10.1177/0261927X09351676

Troboukis, Th., Kiki, K. (2023). 'Political discourse during the two-month election period.' *iMEdD lab*. https://lab.imedd.org/en/o-politikos-logos-kata-ti-dimini- proeklogiki-periodo/

Young T., Hazarika D., Poria S. and Cambria E. (2018), "Recent Trends in Deep Learning Based Natural Language Processing [Review Article]," in *IEEE Computational Intelligence Magazine*, vol. 13, no. 3, pp. 55-75, Aug. 2018

Van Atteveldt, W., Kleinnijenhuis, J., Ruigrok, N., & Schlobach, S. (2008). 'Good news or bad news? Conducting sentiment analysis on dutch text to distinguish between positive and negative relations.' *Journal of Information Technology and Politics*, 5(1): 73–94. doi:10.1080/19331680802154145