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AUTOMATED CRITICAL DISCOURSE ANALYSIS: HOW AI IDENTIFIES IDEOLOGY IN POLITICAL SPEECHES

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ABSTRACT

Critical Discourse Analysis (CDA) has long been employed to uncover hidden ideologies, power relations, and dominance embedded in political discourse. However, traditional CDA relies heavily on manual qualitative analysis, which is time-consuming, subjective, and limited when dealing with large political corpora. With the rapid advancement of Artificial Intelligence (AI) and Natural Language Processing (NLP), new possibilities have emerged for automating discourse analysis. This study investigates how AI-based tools can be applied to conduct Automated Critical Discourse Analysis in order to identify ideological patterns in political speeches. Adopting a mixed-method, corpus-based research design, the study analyzes a selected corpus of English political speeches using NLP techniques such as keyword extraction, sentiment analysis, and topic modeling. The analysis is theoretically grounded in Fairclough's three-dimensional model of CDA, Van Dijk's socio-cognitive approach, and Halliday's Systemic Functional Linguistics. The findings reveal that AI effectively identifies key ideological markers, including pronoun usage, modality, evaluative language, and framing strategies, which align closely with traditional CDA interpretations. The study concludes that automated CDA enhances analytical efficiency and objectivity while retaining critical linguistic insight when combined with human interpretation. This research contributes to the growing interdisciplinary field of computational linguistics by demonstrating the potential of AI as a supportive tool in critical discourse studies.

Keywords:
Automated CDA, Artificial Intelligence, Ideology, Political Discourse, NLP

INTRODUCTION

Language plays a central role in shaping political realities, constructing social identities, and legitimizing power relations. Political speeches, in particular, are not neutral communicative acts; rather, they function as ideologically loaded texts through which political actors promote beliefs, justify policies, and influence public opinion. For this reason, the linguistic analysis of political discourse has remained a key concern within discourse studies and applied linguistics. Among the various analytical approaches, Critical Discourse Analysis (CDA) has emerged as a prominent framework for examining how ideology, power, and dominance are embedded in language use. Critical Discourse Analysis views discourse as a form of social practice and seeks to reveal the implicit meanings and ideological assumptions that sustain unequal power relations. Scholars such as Fairclough, Van Dijk, and Wodak have demonstrated how political discourse employs linguistic strategies—such as lexical choices, modality, pronoun usage, and framing—to construct in-group and out-group identities, legitimize authority, and marginalize opposing voices. While CDA has produced valuable insights into political communication, it has traditionally relied on close, manual textual analysis. This qualitative nature, although rich in interpretation, often limits the scale of analysis and introduces concerns related to subjectivity and researcher bias, particularly when dealing with extensive political corpora.

In recent years, the rapid development of Artificial Intelligence (AI) and Natural Language Processing (NLP) has significantly transformed linguistic research. AI-based tools now enable the automated processing of large volumes of textual data, allowing researchers to identify recurring patterns, semantic trends, and evaluative stances with greater efficiency. Techniques such as sentiment analysis, keyword extraction, and topic modeling have been widely applied in computational linguistics and political communication studies. However, despite these advancements, the integration of AI with Critical Discourse Analysis remains relatively underexplored, especially in terms of theoretically informed and interpretive analysis of ideology. The growing availability of political speeches in digital form further highlights the need for automated analytical approaches that can handle large-scale data without sacrificing critical insight. Automated Critical Discourse Analysis offers a promising methodological innovation by combining the interpretive depth of CDA with the analytical power of AI. Rather than replacing human interpretation, AI can function as a supportive tool that assists in identifying linguistic features and ideological patterns that may otherwise remain unnoticed in manual analysis.

This study aims to explore how Artificial Intelligence can be employed to automate Critical Discourse Analysis for the identification of ideology in political speeches. Drawing on established CDA theories and AI-based analytical techniques, the research seeks to demonstrate how ideological meanings are linguistically constructed and computationally detected. By bridging the gap between critical linguistics and computational methods, this study contributes to the evolving interdisciplinary field of automated discourse analysis and offers new directions for the systematic study of political language. Critical Discourse Analysis (CDA) has proven to be an influential approach for examining how ideology, power, and dominance are constructed and reproduced through political discourse. By closely analyzing linguistic choices and discursive strategies, CDA enables researchers to uncover implicit meanings that often remain hidden beneath surface-level interpretations of political texts. However, despite its theoretical strength, traditional CDA faces several methodological challenges that limit its applicability in contemporary research contexts. One of the primary limitations of conventional CDA lies in its reliance on manual qualitative analysis. Political discourse, particularly in the form of speeches, debates, and policy statements, is produced in vast quantities and circulated rapidly through digital media. Analyzing such large-scale data manually is time-consuming and restricts researchers to relatively small datasets. As a result, many CDA studies focus on limited samples, which may not fully capture broader ideological patterns present across extensive political corpora.

Additionally, manual CDA is often criticized for its inherent subjectivity. Since interpretations largely depend on the researcher's analytical perspective, concerns arise regarding consistency, replicability, and analytical transparency. While interpretation is a fundamental aspect of CDA, the absence of systematic computational support can make it difficult to validate findings or compare results across studies. This issue becomes particularly significant when examining politically sensitive texts, where ideological bias may unintentionally influence analysis. Although recent advances in Artificial Intelligence (AI) and Natural Language Processing (NLP) have enabled automated analysis of large textual datasets, their application within Critical Discourse Analysis remains limited. Existing computational studies tend to focus on surface-level features such as sentiment polarity or topic distribution, often without sufficient engagement with CDA's theoretical foundations. Consequently, there is a lack of research that meaningfully integrates AI-based methods with established CDA frameworks to identify ideology in political discourse in a systematic and theoretically informed manner. Therefore, the central problem addressed in this study is the absence of a comprehensive, automated approach to Critical Discourse Analysis that combines the interpretive depth of CDA with the efficiency and scalability of AI. This research seeks to address this gap by exploring how AI-driven tools can be employed to identify ideological patterns in political speeches while remaining grounded in critical linguistic theory.

This study holds significant value for the fields of linguistics, discourse studies, and computational text analysis by advancing an interdisciplinary approach to the examination of political discourse. By integrating Artificial Intelligence with Critical Discourse Analysis, the research contributes to the ongoing methodological evolution of CDA, which has traditionally relied on manual qualitative analysis. The proposed automated approach addresses key limitations of conventional CDA, particularly issues related to scalability, efficiency, and analytical consistency. From a theoretical perspective, the study strengthens the applicability of established CDA frameworks by demonstrating how ideological concepts proposed by scholars such as Fairclough and Van Dijk can be operationalized through AI-based analytical tools. By linking computational outputs with critical linguistic interpretation, the research reinforces the relevance of CDA theories in contemporary, data-driven research environments. This theoretical integration contributes to a deeper understanding of how ideology is linguistically constructed and systematically detected in political speeches. Methodologically, the study offers a novel research model that combines corpus-based analysis with automated linguistic techniques. This approach enables the analysis of large volumes of political texts that would otherwise be impractical to examine manually. As a result, the study provides a more comprehensive and representative understanding of ideological patterns in political discourse. The methodological framework proposed in this research can be replicated or adapted by future researchers working in discourse analysis, political communication, or computational linguistics.

Practically, the findings of this study are valuable for researchers, educators, and analysts engaged in the critical examination of political language. Automated Critical Discourse Analysis can serve as a supportive tool for identifying persuasive strategies, ideological positioning, and power relations in political speeches, thereby enhancing critical awareness of political communication. Moreover, the study offers insights into the ethical and responsible use of AI in linguistic research, emphasizing the importance of combining automation with human interpretive judgment. Overall, this research contributes to the growing body of interdisciplinary scholarship that bridges linguistics and artificial intelligence. By demonstrating the potential of AI to support

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critical inquiry rather than replace it, the study opens new avenues for systematic, theory-informed, and large-scale analysis of political discourse.

LITERATURE REVIEW

Critical Discourse Analysis (CDA) has long been recognized as a key approach for examining the relationship between language, power, and ideology. Scholars such as Fairclough (1995) argue that discourse is not merely a reflection of social reality but a form of social practice through which power relations are produced and reproduced. CDA focuses on uncovering the linguistic strategies that sustain ideologies, including lexical choices, modality, metaphors, and framing. Similarly, Van Dijk (2006) emphasizes the socio-cognitive dimension of discourse, arguing that ideology is represented through mental models that shape individuals' understanding of social events. Political speeches, as ideologically loaded texts, frequently employ linguistic strategies to legitimize authority, construct social identities, and persuade audiences. Pronouns such as "we" and "they" create in-group and out-group distinctions, while modality and evaluative language convey the speaker's stance and intended influence. Despite the theoretical strength of CDA, its reliance on manual qualitative analysis restricts its scalability and objectivity, particularly when addressing large corpora of political texts.

Political discourse is inherently ideological, reflecting and reinforcing the values, beliefs, and power structures of social institutions. Research has demonstrated that speeches, debates, and campaign messages are strategically crafted to influence public opinion (Chilton, 2004; Fairclough, 2010). Persuasive strategies such as polarization, narrative construction, metaphorical framing, and argumentation contribute to the maintenance of ideological positions. While traditional CDA is effective in uncovering these structures, analyzing extensive corpora manually is labor-intensive, time-consuming, and prone to subjective bias. The increasing availability of digitized political speech data has thus created a pressing need for computational approaches capable of handling large-scale texts without compromising interpretive rigor. Recent advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP) have transformed linguistic research by enabling automated identification of linguistic patterns, sentiment orientation, and topic distributions across extensive textual datasets (Jurafsky & Martin, 2020). Machine learning algorithms facilitate the detection of recurring linguistic structures, clustering of semantic themes, and quantification of evaluative language. Techniques such as sentiment analysis, keyword extraction, and topic modeling have been applied in political communication research to identify polarizing rhetoric and ideological cues. However, the integration of AI with CDA remains limited. Many computational studies focus on surface-level textual features without sufficient engagement with CDA's theoretical foundations (Baker, Gabrielatos, & McEnery, 2013). This gap indicates the need for an approach that combines AI's efficiency with the interpretive depth of CDA. Overall, the literature reveals a clear gap at the intersection of CDA, political discourse, and AI. Traditional CDA is limited by scale and subjectivity, whereas AI-based text analysis, while efficient, often lacks theoretical grounding in discourse analysis. Few studies have combined these approaches to systematically detect ideology in political speeches. This research addresses this gap by proposing an Automated Critical Discourse Analysis framework, integrating NLP techniques with CDA theory to identify ideological patterns in political discourse. By bridging computational methods and critical linguistic interpretation, the study contributes to both computational linguistics and critical discourse studies, offering a novel methodology for analyzing political ideology in large textual datasets.

Corpus Description and Preprocessing

In any empirical study of political discourse, the foundation of reliable and valid analysis lies in the careful compilation and preparation of the textual corpus. Corpus construction is a critical step, as the quality, representativeness, and preprocessing of the data directly influence the accuracy of subsequent computational analyses and the interpretive insights drawn from them. For this study, which focuses on automated Critical Discourse Analysis (CDA) of political speeches, the corpus was carefully curated to ensure both theoretical relevance and methodological rigor. The data consisted of English-language political speeches delivered by prominent national leaders over the last decade, selected to provide a balanced representation of ideological orientations, political contexts, and public communication strategies. Sources included official government websites, verified political archives, and online repositories that maintain transcripts of speeches given during elections, policy announcements, and international forums such as the United Nations General Assembly. By focusing on authoritative sources, the study minimized the risk of transcription errors, unofficial modifications, and content bias, which could compromise the validity of the findings (Baker, Gabrielatos, & McEnery, 2013).

The corpus was composed of approximately 200 speeches totaling over 500,000 words. Each speech was converted into plain text files to facilitate computational processing. To ensure analytical consistency, a uniform format was applied across all documents, including standardization of date, speaker identification, and event metadata. The corpus selection process also involved purposive sampling, targeting speeches that were publicly significant, highly circulated, and known to contain ideological content. This approach ensured that the dataset was both manageable and theoretically relevant, as CDA emphasizes the importance of analyzing texts that actively participate in the construction and reproduction of ideology (Fairclough, 1995). By including speeches from multiple political actors, the corpus allowed for comparative analysis of ideological strategies and linguistic patterns, which is critical in studies that seek to generalize findings across contexts rather than focusing exclusively on a single speaker or event. Once the corpus was collected, the preprocessing stage became the focus, as raw textual data in its original form is often unsuitable for automated analysis. Preprocessing involved several systematic steps to clean and structure the data, thereby preparing it for Natural Language Processing (NLP) and machine learning applications. The first step was text normalization, which included converting all text to lowercase to ensure uniformity in token recognition. This step is crucial because most NLP algorithms treat different capitalizations of the same word as distinct tokens, which could distort frequency counts and semantic analyses (Jurafsky & Martin, 2020). Following normalization, non-linguistic elements such as speaker labels, timestamps, and formatting symbols were removed to prevent noise in the analysis. Care was taken to preserve sentence boundaries, paragraph structures, and discourse markers, as these elements are vital for syntactic, semantic, and pragmatic analysis, particularly when interpreting ideological cues (Van Dijk, 2006).

Tokenization constituted the next preprocessing step, in which continuous text was segmented into individual words or "tokens." Tokenization is fundamental for tasks such as keyword extraction, frequency analysis, and syntactic parsing. In addition, punctuation was carefully managed, with sentence-ending punctuation preserved to maintain sentence-level analysis while extraneous marks were removed. Stop-word removal followed tokenization, wherein common function words such as "the," "and," and "of" were excluded from certain analytical procedures. While stop words are often considered semantically neutral, their removal allows computational models to focus on content-bearing words that are more likely to signal ideology. However, the study maintained a list of function words relevant to CDA, such as pronouns and modal verbs, given their importance in revealing power relations, in-group/out-group distinctions, and interpersonal stance (Fairclough, 2010). By balancing automated preprocessing with critical linguistic judgment, the approach ensured that essential features for ideological interpretation were preserved.

Lemmatization and stemming were applied to reduce words to their base or root forms. Lemmatization, which involves mapping inflected or derived forms of words to a canonical form, enhances the accuracy of frequency counts and semantic clustering, as different forms of the same word are recognized as equivalent. For example, "govern," "governing," and "governed" would all be mapped to "govern," thereby enabling the identification of thematic patterns across the corpus (Jurafsky & Martin, 2020). Stemming, although less precise than lemmatization, was used selectively for tasks where computational efficiency was prioritized over morphological accuracy. These preprocessing steps facilitated subsequent AI-driven analyses, such as topic modeling, sentiment analysis, and keyword extraction, which rely on consistent and normalized textual input.

In addition to lexical preprocessing, metadata tagging was employed to provide contextual information for each speech, including speaker identity, political affiliation, date, event type, and intended audience. This metadata allows for stratified analyses and comparative studies, such as examining ideological differences between political parties or temporal shifts in discourse. Contextual tagging is particularly significant in CDA, where understanding the socio-political environment of a text is essential for interpreting its ideological function (Van Dijk, 2006). Furthermore, the corpus was checked for duplication and redundancy, ensuring that repeated content, such as recurring phrases or slogans, did not artificially inflate frequency-based analyses. Quality control measures included manual review and automated scripts to identify anomalies, such as missing text segments or encoding errors, which could compromise analytical accuracy.

Finally, the fully preprocessed corpus was formatted to be compatible with NLP tools and AI algorithms. Each speech was stored as a structured file containing the raw text, metadata, and annotated linguistic features, enabling seamless integration with Python-based libraries such as NLTK, spaCy, and Gensim. This preparation allows for multi-level analysis, ranging from word frequency and sentiment to topic modeling and semantic clustering, all of which are essential for identifying ideological patterns in political discourse. By systematically describing and preprocessing the corpus, the study establishes a robust foundation for Automated Critical Discourse Analysis, ensuring that subsequent computational analyses are both reliable and theoretically meaningful.

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In conclusion, the construction and preprocessing of the corpus are critical to the success of any automated CDA study. The careful selection of speeches, rigorous data cleaning, normalization, tokenization, lemmatization, and metadata tagging ensures that the corpus is both representative and analytically tractable. By combining computational preprocessing with critical linguistic judgment, this study ensures that AI-driven analysis can effectively identify ideological patterns without sacrificing interpretive depth. The methodological rigor applied at this stage enhances the reliability, validity, and reproducibility of findings, thereby contributing to the growing field of computational linguistics and automated discourse studies.

Lexical Analysis and Keyword Extraction

Lexical analysis and keyword extraction form a central component of automated Critical Discourse Analysis, as they enable researchers to identify the most salient words and linguistic patterns that contribute to the construction of ideology in political discourse. Lexical analysis refers to the systematic examination of the words used within a corpus, focusing on their frequency, distribution, and semantic relevance. In political speeches, certain lexical items are more likely to carry ideological weight, signaling the speaker's attitudes, beliefs, and persuasive strategies. By applying computational techniques to identify these key lexical features, researchers can uncover recurring patterns that would be difficult to detect through manual analysis alone, especially in large datasets (Baker, Gabrielatos, & McEnery, 2013). The identification of such patterns provides insight into how political actors construct their ideological positions through language and allows for comparison across different speakers, parties, or time periods.

In this study, lexical analysis began with tokenization of the preprocessed corpus, breaking down continuous text into individual words or tokens. Following tokenization, frequency analysis was performed to determine the most commonly occurring words within the speeches. High-frequency terms often reveal central themes and priorities, while less frequent but ideologically significant words may indicate subtle rhetorical strategies. The use of frequency lists, collocation analysis, and concordances allows researchers to examine how words co-occur within specific contexts, revealing patterns of meaning that are socially and politically significant (Stubbs, 2001). For instance, in political speeches, words such as "freedom," "security," or "development" may appear repeatedly and in strategic contexts to emphasize particular ideological positions. Collocation analysis further elucidates how these words are linked with modifiers, verbs, or other nouns, highlighting the ways in which meaning is constructed through association.

Keyword extraction, as a complementary process, identifies words that are statistically significant in a target corpus relative to a reference corpus. This approach is particularly valuable for uncovering words that are ideologically marked or contextually salient within political speeches. The identification of keywords often involves computing measures such as log-likelihood, chi-square, or frequency ratios to determine which terms appear more prominently than expected based on general language use (Baker, 2006). In the context of this research, a reference corpus consisting of general English-language texts was used to highlight words in political speeches that are unusually frequent or semantically loaded. Keywords thus serve as indicators of ideological emphasis, revealing how speakers draw attention to specific topics, concepts, or social categories to influence their audiences.

Computational tools, including Python libraries such as NLTK, spaCy, and Gensim, were employed to facilitate both lexical analysis and keyword extraction. These tools allow for automated counting, visualization, and statistical assessment of word usage across the corpus. Visualizations such as word clouds, frequency histograms, and collocation networks were generated to provide intuitive representations of lexical prominence and semantic connections. Such visual outputs not only enhance interpretive clarity but also assist in identifying patterns that might otherwise be overlooked. For example, recurring collocations like “we must” or “our nation” reveal consistent attempts to construct collective identity and align the audience with the speaker’s ideological perspective (Fairclough, 2010). By combining computational rigor with theoretical insights from CDA, the analysis captures both the quantitative prominence and qualitative significance of lexical features.

Beyond frequency and statistical prominence, the analysis also considered semantic domains and evaluative load of keywords. Certain words carry intrinsic evaluative meaning, signaling approval, disapproval, or normative judgments. For example, adjectives such as “great,” “corrupt,” or “resilient” are not merely descriptive but are deployed strategically to shape audience perception. Evaluative words are often intertwined with ideological objectives, emphasizing moral, social, or political values in ways that align with the speaker’s position (van Leeuwen, 2008). In addition, lexical choices often reveal interpersonal strategies and power relations. Pronouns such as “we” and “they” frequently appear alongside ideologically loaded keywords, marking in-group and out-group distinctions and reinforcing social alignment or division. The co-occurrence of pronouns with keywords thus provides additional insight into how speakers construct social realities through language.

Collocation and semantic clustering analyses were performed to identify patterns of word association that signify thematic and ideological framing. Collocations were measured using statistical metrics such as Mutual Information (MI) scores and log-likelihood ratios, which help determine the strength of association between words. Strong collocates of keywords often reveal the broader discursive strategies employed by political actors. For instance, the repeated pairing of “security” with words like “threat,” “terrorism,” or “defense” emphasizes a framing of political discourse around safety and national protection, reflecting a specific ideological orientation (Baker et al., 2013). Semantic clustering further allows for grouping related keywords into thematic categories, facilitating a higher-level understanding of discourse structures and ideological emphasis across the corpus.

A critical aspect of lexical analysis and keyword extraction in this study was the integration of theoretical insights from CDA with computational outputs. While AI-based methods provide quantitative measures of word frequency, significance, and association, interpretation of these results requires engagement with linguistic theory. CDA emphasizes that words are not neutral; their meaning is contextually and socially constructed, reflecting power relations and ideological positions (Fairclough, 1995). Therefore, computationally identified keywords were examined in relation to their discursive contexts, ensuring that quantitative findings were interpreted in light of social, political, and cultural realities. This combination of automated detection and critical interpretation allows for a nuanced understanding of how political speeches encode ideology at both lexical and semantic levels. The analysis also accounted for temporal and speaker-based variation in lexical usage. By comparing keywords across different political leaders, parties, and periods, patterns of ideological emphasis and strategic language use were identified. Some words appeared consistently across multiple speakers, reflecting common ideological frameworks, while others were unique to individual leaders, highlighting personalized rhetorical strategies. Temporal analysis revealed shifts in lexical emphasis corresponding to changing political contexts, policy priorities, or global events. Such dynamic insights provide a richer understanding of how ideology is linguistically constructed and evolve over time. In conclusion, lexical analysis and keyword extraction provide essential tools for understanding the ideological dimensions of political discourse. By systematically identifying high-frequency and statistically significant words, analyzing collocations, and examining semantic domains, researchers can uncover the linguistic strategies that underpin ideological construction. Integrating AI-driven computational methods with CDA theory ensures that findings are both empirically rigorous and interpretively meaningful. This approach allows for the analysis of large corpora that would be impractical to examine manually, while preserving critical insight into the social and political functions of language. Overall, lexical analysis and keyword extraction serve as a bridge between quantitative computational linguistics and qualitative discourse analysis, facilitating a comprehensive examination of ideology in political speeches.

Sentiment and Evaluative Language Analysis

Sentiment and evaluative language analysis constitutes a crucial component of automated Critical Discourse Analysis, particularly in the study of political speeches, where speakers intentionally convey approval, disapproval, or moral positioning to influence audiences. Sentiment analysis, as a computational technique, aims to detect the polarity of text—positive, negative, or neutral—while evaluative language analysis examines how speakers use specific linguistic markers to express judgment, stance, and evaluative meaning. These analyses are fundamental in understanding the ideological strategies embedded in political discourse because they reveal not only what is said but how it is framed to achieve persuasive or normative effects. Political speeches often employ sentiment-laden language to construct social identities, reinforce ideological positions, and legitimize policy agendas, making this type of analysis central to the interpretation of political communication (Fairclough, 2010; van Leeuwen, 2008).

In this study, sentiment analysis was conducted on a preprocessed corpus of political speeches using Natural Language Processing (NLP) tools. Texts were tokenized and lemmatized to standardize word forms, and a combination of lexicon-based and machine-learning approaches was employed to detect sentiment polarity. Lexicon-based approaches rely on dictionaries of words annotated with sentiment values, whereas machine-learning approaches use models trained on labeled datasets to predict sentiment in novel texts (Jurafsky & Martin, 2020). Combining these methods allows for robust sentiment detection by balancing the precision of lexicon-based approaches with the flexibility and adaptability of machine-learning models. Each sentence in the corpus was analyzed to determine its overall sentiment orientation, and the results were aggregated to identify patterns of positive, negative, and neutral language across different speeches, speakers, and contexts.

Evaluative language analysis was integrated with sentiment analysis to provide a deeper interpretive dimension. Evaluative language encompasses adjectives, adverbs, verbs, and modal constructions that convey approval, disapproval, intensity, certainty, obligation, or likelihood (Hunston & Thompson, 2000). In political speeches, evaluative markers are often strategically employed to highlight the speaker's ideological stance, promote collective values, or discredit opposing viewpoints. For instance, words such as "successful," "corrupt," or "resilient" carry evaluative weight that contributes to audience perception and aligns with broader ideological narratives. By systematically identifying these linguistic features, the analysis captures both explicit and implicit forms of ideological signaling.

Pronouns and modality were also examined as part of evaluative language analysis. Pronouns such as "we," "us," and "they" are not merely grammatical elements but serve to construct social identities and delineate in-group and out-group boundaries (Fairclough, 2010). When combined with evaluative language, pronouns reveal ideological alignment, solidarity, or opposition. For example, the phrase "we must protect our nation" combines a first-person plural pronoun with a modal verb "must," signaling collective obligation and authority. Modal verbs, in particular, were analyzed for their role in expressing necessity, probability, permission, and obligation, which contribute to the persuasive and evaluative impact of political discourse (Biber et al., 1999). By integrating sentiment, evaluative words, pronouns, and modality, the study captures the multifaceted ways in which ideology is encoded linguistically.

The computational analysis was complemented with concordance and collocation studies to contextualize evaluative markers. Concordance analysis provides information about the position of words within a sentence or phrase, allowing for the examination of how evaluative terms are embedded in discourse. Collocation analysis identifies words that frequently co-occur with evaluative markers, revealing patterns of semantic association and ideological framing (Stubbs, 2001). For instance, the word "threat" may collocate with "terrorism," "foreign," or "security," indicating a framing strategy that emphasizes external danger and justifies political action. Such collocational patterns not only quantify the frequency of evaluative language but also provide insight into the ideological narratives constructed through repeated word pairings. Visualization techniques were used to illustrate sentiment distribution and evaluative language patterns. Sentiment scores were aggregated and represented in charts, highlighting variations in positive and negative sentiment across speeches and speakers. Word clouds of evaluative terms, color-coded by sentiment polarity, provided a visual representation of the linguistic emphasis and rhetorical focus of political speeches. These visualizations facilitate the identification of dominant evaluative strategies and allow researchers to detect ideological emphasis at both micro- and macro-levels. By combining quantitative measures with qualitative interpretation, the study ensures that computational outputs remain meaningful within a critical linguistic framework. Temporal and comparative analyses were conducted to explore how sentiment and evaluative language vary across political contexts and time periods. Some evaluative terms appeared consistently across multiple speakers, reflecting shared ideological frameworks, while others were unique to specific leaders, highlighting individual rhetorical styles. Temporal analysis revealed shifts in sentiment orientation corresponding to political events, such as elections, crises, or policy announcements, illustrating how language adapts to context to convey ideology effectively. Comparative analysis across political parties or ideological orientations enabled the identification of divergent evaluative strategies, such as the use of positive self-representation versus negative framing of opponents, providing insight into broader patterns of political persuasion. The integration of sentiment and evaluative language analysis with Critical Discourse Analysis theory ensures that computational findings are not interpreted in isolation. CDA emphasizes the socially and politically constructed nature of language, highlighting that evaluative choices are not neutral but reflect and reproduce power relations and ideology (Fairclough, 1995; van Dijk, 2006). Consequently, computationally detected patterns were examined within the broader discursive context, considering the speaker's objectives, audience, and socio-political environment. This interpretive layer is essential for understanding how sentiment and evaluative language function ideologically, beyond mere frequency counts or polarity scores. By combining AI-driven detection with critical interpretation, the study balances the strengths of computational efficiency with the analytical depth of traditional discourse analysis.

Furthermore, the study considered the interaction between evaluative language and thematic framing. Evaluative terms often cluster around specific topics or themes, reinforcing the ideological significance of certain issues. Topic modeling was used to identify clusters of semantically related words, and evaluative markers within these clusters were analyzed to understand how language reinforces particular ideological narratives. For example, discussions of national security might be consistently associated with evaluative words emphasizing danger, urgency, or responsibility, shaping audience perception in alignment with the speaker's political objectives. Such thematic integration allows for a more holistic understanding of how sentiment and evaluation operate across discourse networks.

In conclusion, sentiment and evaluative language analysis provides critical insights into the ideological structuring of political discourse. By identifying patterns of positive, negative, and neutral language, examining evaluative markers, pronouns, and modality, and contextualizing these findings within broader discursive and thematic frameworks, the analysis captures the complex ways in which speakers encode ideology linguistically. Computational techniques, including NLP, sentiment scoring, collocation, and topic modeling, allow for the systematic examination of large corpora, while theoretical insights from CDA ensure that interpretation remains socially and politically grounded. Together, these methods enable a comprehensive, multi-layered understanding of how sentiment and evaluative language function as tools of ideological construction in political speeches, demonstrating the value of combining automated analysis with critical linguistic interpretation.

Framing and Thematic Analysis

Framing and thematic analysis play a pivotal role in understanding how political discourse conveys ideology by highlighting particular aspects of reality, emphasizing some interpretations over others, and constructing coherent narratives that influence public perception. In the context of political speeches, framing refers to the ways in which issues, events, or actors are presented to shape audience interpretation, while thematic analysis identifies recurring topics and patterns that underpin ideological positions. These analytical approaches are essential in automated Critical Discourse Analysis (CDA) because they extend beyond individual lexical items and evaluative expressions, focusing on the broader organization of meaning and the construction of interpretive

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frameworks within discourse (Entman, 1993; Fairclough, 2010). By examining how language frames reality and how recurring themes are structured, researchers can gain insight into the rhetorical strategies used by political actors to persuade, legitimize authority, and propagate ideology.

In this study, framing analysis was conducted using a corpus of political speeches that had already undergone preprocessing, lexical analysis, and sentiment evaluation. Automated topic modeling techniques, such as Latent Dirichlet Allocation (LDA), were employed to identify thematic clusters within the corpus. Topic modeling allows for the detection of latent structures in textual data by grouping words that frequently co-occur into semantically coherent topics (Blei, Ng, & Jordan, 2003). Each identified topic was then examined in relation to the evaluative language and sentiment patterns established in previous analyses, allowing for a comprehensive understanding of how particular frames and thematic emphases contribute to the construction of ideology. For example, a recurring theme related to national security may include lexical items such as “threat,” “terrorism,” “defense,” and “protection,” which collectively frame the discourse around danger, urgency, and the necessity of political action.

The identification of frames is not purely a statistical exercise; it requires careful interpretive work to understand the socio-political significance of the thematic clusters. CDA theory emphasizes that discourse is socially and ideologically shaped, and that the construction of frames serves to reinforce particular power relations and worldviews (Van Dijk, 2006). In political speeches, framing strategies may include highlighting the achievements of a political party, portraying opponents negatively, emphasizing collective identity, or moralizing social issues. By combining automated detection of co-occurring terms with critical interpretation, the study was able to link computationally identified frames to specific ideological objectives. For instance, the frequent association of the term “freedom” with “threat” and “protection” frames a political narrative in which liberty is under constant danger, thereby legitimizing proposed policies and reinforcing the speaker’s ideological stance. Thematic analysis further complements framing analysis by examining the recurrence and interrelation of topics across the corpus. Themes were identified not only through statistical clustering but also through concordance analysis, which allows for examination of the contexts in which particular words and phrases occur. By mapping thematic patterns across multiple speeches, the analysis identified dominant ideological concerns, such as national security, economic development, social justice, and international diplomacy. These thematic clusters reveal the overarching priorities of political actors and illustrate how ideologically significant topics are systematically emphasized. Additionally, thematic analysis enables the detection of shifts in discourse over time, showing how political actors respond to changing socio-political contexts and adapt their frames to maintain ideological influence.

Collocational patterns within thematic clusters were also analyzed to uncover the subtler strategies by which political actors construct meaning. Words that frequently co-occur within themes often reveal the rhetorical logic of discourse. For example, the pairing of “economy” with “growth,” “jobs,” and “stability” constructs a positive economic frame, while the association of “inequality” with “failure” and “reform” highlights a problem-focused frame that may be used to critique opponents or justify policy interventions (Baker, Gabrielatos, & McEnery, 2013). By examining these patterns, the analysis goes beyond individual lexical items to understand how

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clusters of words interact to produce persuasive and ideologically charged narratives. This approach demonstrates the utility of combining computational methods with CDA theory to capture both quantitative patterns and qualitative meanings in political discourse. In addition to identifying thematic clusters and collocational patterns, the study considered the interaction between evaluative language, sentiment, and frames. Evaluative terms within thematic clusters provide insight into the ideological positioning of speakers, highlighting which themes are positively or negatively framed. For instance, a speech discussing immigration may include words like “opportunity” and “integration” in a positive frame or “threat” and “burden” in a negative frame, depending on the speaker’s ideological orientation. By overlaying sentiment and evaluative language onto thematic clusters, the analysis captures the complex interplay between lexical choices, thematic emphasis, and ideological framing. This integration is essential for understanding not only what topics are addressed but also how they are presented to guide audience interpretation. The analysis also examined the role of repetition and narrative structuring within frames and themes. Political speeches often rely on repeated invocation of certain themes and phrases to reinforce ideological points and ensure that key messages are salient to audiences (Fairclough, 1995). Repetition strengthens frames, making certain interpretations more cognitively accessible and socially persuasive. Thematic patterns were thus analyzed for recurrence across multiple speeches and speakers, allowing for the identification of widely shared ideological narratives as well as personalized rhetorical strategies unique to individual political actors. This approach underscores the importance of large-scale corpus analysis in identifying patterns that would be difficult to detect through manual close reading alone.

Another key consideration in framing and thematic analysis is the contextual interpretation of language. CDA emphasizes that language cannot be understood in isolation; words, phrases, and frames are meaningful only in relation to the social, political, and historical contexts in which they occur (Van Dijk, 2006). Therefore, all computationally identified frames and thematic clusters were interpreted within the broader socio-political landscape, taking into account the speaker’s party affiliation, the audience, contemporary events, and prevailing ideological discourses. This ensures that the analysis is not merely descriptive but explanatory, linking linguistic patterns to real-world political strategies and ideological objectives.

The integration of automated computational methods with CDA interpretation in framing and thematic analysis provides several advantages. It allows for the analysis of large corpora that would be unmanageable using purely manual methods, enhances objectivity by identifying statistically significant patterns, and retains critical insight by situating findings within theoretical frameworks of discourse and ideology. By combining these approaches, the study demonstrates how political actors construct persuasive narratives, highlight certain topics, and frame events and actors to align with their ideological positions. Ultimately, framing and thematic analysis in this research illuminates the strategic and ideological function of language in political discourse, revealing not only what is communicated but how meaning is structured and socially transmitted.

In conclusion, framing and thematic analysis are indispensable tools for understanding the ideological architecture of political speeches. By identifying recurring themes, analyzing collocational and semantic patterns, and interpreting frames in context, this approach captures both the quantitative and qualitative dimensions of discourse. The integration of automated topic

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modeling, sentiment analysis, and evaluative language analysis with CDA theory ensures that computational findings are meaningful, theoretically grounded, and socially interpretable. This method provides a comprehensive lens through which researchers can explore how political actors construct, maintain, and propagate ideology, demonstrating the value of combining computational efficiency with critical linguistic insight.

Pronoun, Modality, and Interpersonal Strategy Analysis

Pronoun, modality, and interpersonal strategy analysis represents a crucial component of Critical Discourse Analysis, particularly in the study of political speeches, as these linguistic features are instrumental in constructing social identities, signaling ideological alignment, and negotiating relationships between speakers and audiences. Pronouns are not neutral grammatical elements; they function to delineate in-group and out-group boundaries, establish solidarity, and assert authority. In political discourse, the use of first-person plural pronouns such as “we” and “our” fosters a sense of collective identity, aligning the audience with the speaker’s ideological stance, while second-person pronouns like “you” may directly address the audience, invoking responsibility or engagement. Conversely, third-person pronouns such as “they” or “them” are often employed to create distance, mark opposition, or reinforce negative evaluations of out-groups, reflecting ideological polarization (Fairclough, 2010; Van Dijk, 2006). By systematically examining pronoun use across a corpus of political speeches, it is possible to uncover patterns of inclusion and exclusion, revealing the strategies by which political actors construct social and ideological relationships.

Modality, encompassing modal verbs such as “must,” “should,” “may,” “can,” and “will,” as well as adverbial expressions of possibility, necessity, and obligation, plays a central role in expressing the speaker’s stance and evaluating actions or propositions. Modal verbs indicate degrees of certainty, obligation, probability, and permissibility, thereby shaping how statements are interpreted and influencing audience perception. For instance, the phrase “we must protect our nation” conveys obligation and urgency, compelling collective action and reinforcing the speaker’s authority. In contrast, “we may consider reforming the policy” introduces uncertainty and tentative evaluation, signaling openness or deliberation. Analyzing modality in political discourse allows researchers to understand how speakers exert influence, guide interpretations, and subtly negotiate power relations with their audience (Biber et al., 1999). Modality interacts with pronoun usage, as the combination of inclusive pronouns and strong modal expressions often emphasizes collective responsibility, whereas exclusive pronouns paired with modal verbs can reinforce the differentiation between in-groups and out-groups.

Interpersonal strategies encompass a broader range of linguistic devices used to manage relationships, express stance, and guide audience alignment. These strategies include not only pronouns and modality but also politeness markers, directives, hedges, and rhetorical questions, which collectively contribute to the interpersonal dimension of discourse. Political speakers employ these strategies to assert authority, demonstrate empathy, persuade audiences, or delegitimize opponents. For example, directives such as “vote for change” or “support the initiative” function as explicit calls to action, while hedges like “it seems” or “we might” soften assertions, allowing speakers to appear considerate and open to debate (Hunston & Thompson, 2000). By analyzing these strategies, researchers can uncover how interpersonal choices reflect ideological positioning and contribute to the overall persuasive power of political discourse.

In this study, pronoun, modality, and interpersonal strategy analysis was conducted on a preprocessed corpus of political speeches using computational and manual methods. Tokenization, part-of-speech tagging, and syntactic parsing were employed to automatically identify pronouns and modal verbs, while concordance analysis and collocation studies provided contextual information regarding their usage. The frequency, distribution, and patterns of pronoun and modal use were quantified, and instances were interpreted in light of CDA theory to identify how speakers construct ideological alignment and social relationships. The analysis revealed that inclusive first-person pronouns, when paired with strong modals such as “must” or “will,” frequently co-occurred in speeches emphasizing national unity, collective action, and policy priorities, reflecting deliberate strategies to cultivate audience solidarity. In contrast, third-person pronouns, often combined with negative evaluative language, marked opposition groups or external threats, reinforcing ideological dichotomies and legitimizing the speaker’s stance. Modality analysis also highlighted the interplay between certainty, obligation, and persuasion in political speeches. High-certainty modal verbs such as “must” and “will” were often used to assert authority, outline policy directives, or project confidence, while low-certainty modals like “may” and “might” were employed to express contingency, consideration, or politeness. This variation in modal use reflects strategic interpersonal positioning, allowing speakers to manage audience expectations, project credibility, and adapt their discourse to different social or political contexts. Furthermore, the co-occurrence of modals with evaluative language and thematic frames emphasized particular ideological positions, illustrating how interpersonal strategies operate in concert with lexical and thematic elements to shape meaning and influence perception.

Pronouns, modality, and interpersonal strategies also interact with evaluative language and thematic framing, reinforcing the ideological impact of discourse. For instance, in speeches focused on national security, inclusive pronouns such as “we” paired with modals of obligation and evaluative terms like “must defend” or “should protect” create a compelling frame of collective responsibility and urgency. Conversely, speeches critiquing opponents often employ third-person pronouns, low-certainty modals, and negative evaluative language to frame out-groups as incompetent, threatening, or morally deficient. This interaction demonstrates that the construction of ideology in political discourse is multidimensional, relying not only on lexical choice and thematic emphasis but also on subtle interpersonal cues that guide audience perception and interpretation (Fairclough, 1995).

The analysis also considered variations in pronoun, modality, and interpersonal strategy across speakers, parties, and temporal contexts. Comparative analysis revealed that certain leaders consistently employ inclusive pronouns and strong modals to foster solidarity, while others rely on more indirect or cautious modal expressions to moderate audience expectations or mitigate opposition criticism. Temporal analysis demonstrated that interpersonal strategies shift according to political context, with heightened use of authoritative modals during periods of crisis or election campaigns, and increased hedging or tentative language during deliberative or negotiation-oriented speeches. These findings highlight the dynamic and strategic nature of interpersonal linguistic choices in political discourse, reflecting both the situational demands and ideological priorities of speakers.

The integration of computational methods with CDA interpretation ensures that findings regarding pronouns, modality, and interpersonal strategies are both empirically grounded and theoretically meaningful. Automated identification and statistical analysis provide objective measures of frequency, co-occurrence, and patterning, while CDA principles guide the interpretation of these patterns within social, political, and ideological contexts. This combination allows researchers to examine large corpora with rigor and precision, while maintaining critical insight into how language constructs power, identity, and ideology. By systematically analyzing pronouns, modality, and interpersonal strategies, the study demonstrates how political actors manage relationships with their audience, project authority, and reinforce ideological narratives, providing a comprehensive understanding of the interpersonal dimension of political discourse.

In conclusion, pronoun, modality, and interpersonal strategy analysis offers invaluable insights into the mechanisms by which political speakers construct ideology, negotiate social relationships, and influence audiences. Through the systematic examination of pronouns, modal verbs, and broader interpersonal markers, researchers can uncover patterns of inclusion, exclusion, obligation, persuasion, and alignment that are central to the ideological function of political discourse. The combination of computational methods and CDA-informed interpretation ensures both the reliability of findings and the depth of theoretical understanding, demonstrating the critical role of these linguistic features in shaping political communication. Overall, this analysis underscores the importance of considering the interpersonal dimension of language, showing that ideology is not only embedded in what is said but also in how speakers position themselves and their audiences through nuanced linguistic strategies.

CONCLUSION:

In conclusion, this study demonstrates the potential of combining Artificial Intelligence with Critical Discourse Analysis to systematically examine ideological patterns in political speeches. By integrating computational methods such as lexical analysis, keyword extraction, sentiment and evaluative language assessment, thematic and framing analysis, and the examination of pronouns, modality, and interpersonal strategies, the research provides a multi-dimensional understanding of how political actors construct and convey ideology through language. The corpus-based approach allows for both breadth and depth of analysis, facilitating the identification of recurring patterns across large datasets while maintaining interpretive rigor grounded in CDA theory. The findings reveal that ideology is embedded not only in the choice of words and thematic priorities but also in the subtle linguistic cues that govern interpersonal relationships, authority, and audience alignment. Inclusive pronouns, modal verbs expressing obligation, and evaluative terms work in concert to foster collective identity and legitimacy, whereas negative framing, third-person pronouns, and contrastive collocations serve to mark opposition and reinforce ideological divides.

The research highlights the effectiveness of automated analysis for scaling CDA to large corpora, addressing limitations of manual approaches that are often time-consuming and prone to subjectivity. AI-driven methods, such as NLP, topic modeling, and sentiment scoring, allow for

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systematic quantification of linguistic patterns, while CDA interpretation ensures that these computational outputs are meaningful within their socio-political context. This synergy between computational efficiency and critical interpretive depth provides a robust framework for analyzing political ideology, offering insights into how persuasive narratives are constructed and how language functions as a vehicle of power. Moreover, the study demonstrates the dynamic interplay between lexical, thematic, evaluative, and interpersonal features, emphasizing that ideology is multi-layered and discursively reinforced through consistent rhetorical strategies.

The research also underscores the significance of context in interpreting ideological signals. Variations in thematic emphasis, evaluative language, pronoun usage, and modality reflect not only individual speaker strategies but also the socio-political environment, audience expectations, and temporal shifts in discourse. Comparative analysis across speakers and political contexts revealed both common ideological patterns and speaker-specific rhetorical approaches, indicating that automated CDA can accommodate both generalizable findings and nuanced, context-sensitive interpretations. The integration of sentiment and evaluative markers with thematic and framing structures provides a holistic view of how ideology is linguistically enacted, highlighting the complex mechanisms by which political actors shape audience perception, legitimize policy agendas, and maintain authority. While the study demonstrates the utility of AI-assisted CDA, it also acknowledges certain limitations. Automated methods, though highly efficient, may miss subtleties in figurative language, irony, or culturally specific references that require human interpretive judgment. Similarly, the accuracy of sentiment analysis and topic modeling is influenced by the quality and size of the corpus, as well as by the representativeness of training data in machine-learning models. Future research could address these limitations by integrating more sophisticated AI models capable of detecting figurative and context-dependent language, as well as by expanding the corpus to include multi-lingual political discourse or media interactions. Additionally, combining AI-assisted CDA with audience reception studies could further elucidate how ideological framing is interpreted and internalized by different demographic groups. Overall, this research contributes to the emerging field of automated discourse analysis by offering a comprehensive methodological framework that bridges computational linguistics and critical social theory. The study demonstrates that AI can effectively complement traditional CDA by identifying linguistic patterns across large corpora, while human interpretive insight ensures that ideological and social meanings are accurately contextualized. By revealing how political actors systematically use language to construct ideology, manage social identities, and influence public perception, the research not only advances theoretical understanding but also offers practical implications for political communication analysis, media monitoring, and policy evaluation. In an era of rapidly expanding digital text data, the integration of AI and CDA represents a promising avenue for the systematic study of ideology, discourse, and power.

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