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# MACHINE LEARNING AND THE STUDY OF LANGUAGE CHANGE: A REVIEW OF METHODOLOGIES AND APPLICATION

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K e y w o r d s

*Language Change*
*Machine Learning*
*Historical Linguistics*
*Sociolinguistics*
*Language Contact*
*Computational Linguistics*

A B S T R A C T

Language change, a fundamental aspect of human communication, has long been a central focus in linguistic research. Traditional methods of analysis, while valuable, have been limited by the scale and complexity of linguistic data. The advent of machine learning (ML) offers transformative potential in this field, enabling the analysis of vast datasets and the discovery of subtle patterns that may elude manual scrutiny. This review paper comprehensively examines the current state of ML methodologies in the study of language change, synthesizing findings from 67 peer-reviewed articles. We delve into diverse ML approaches, including supervised, unsupervised, and deep learning techniques, and critically evaluate their applications across various linguistic domains, such as historical linguistics, sociolinguistics, and language contact. We address challenges related to data availability, bias, and model interpretability, emphasizing the need for transparent and rigorous methodologies. By summarizing key findings and outlining future directions, this review aims to foster interdisciplinary collaboration between linguists and computer scientists, advancing our understanding of the complex dynamics of language evolution.

## 1 Introduction

Language is a fundamental human communication and cognition component, marked by its dynamic and ever-evolving nature. It experiences continuous transformations across various linguistic dimensions—phonological, morphological, syntactic, semantic, and pragmatic—and these transformations occur over diverse timescales, from generational shifts to developments spanning centuries (Granlund et al., 2021). While vital to the essence of language, this inherent dynamism poses significant challenges for researchers dedicated to understanding and modeling the complex processes underlying language change. The traditional approach to studying language change has predominantly involved the detailed analysis of relatively limited textual corpora, relying heavily on the expertise of linguists to identify and trace the patterns and trajectories of linguistic evolution (Hossain et al., 2024). With the emergence of machine learning (ML), new methodologies have become available, revolutionizing the potential for research in this field. Machine learning offers innovative tools and fresh perspectives that leverage the power of computational analysis, allowing for the exploration of language change with unprecedented depth and breadth (Jordan & Mitchell, 2015). These advancements promise to enhance our understanding by facilitating the examination of vast datasets and the detection of subtle linguistic patterns that might otherwise remain undiscovered (Khouja, 2020; Kratzwald et al., 2018).

Machine learning, an integral subfield of artificial intelligence, is dedicated to developing algorithms that empower computers to learn from and make predictions or decisions based on data (Leavitt et al., 2021). This capability is particularly significant in the context of language change research, where ML algorithms can be applied to a wide array of linguistic datasets. These datasets range from historical texts and social media posts to spoken language corpora, enabling the identification of subtle patterns, correlations, and trends that traditional analytical methods might miss (Matykiewicz et al., 2009). The potential of ML to handle diverse and voluminous data sets significantly enhances the analytical capabilities in linguistic studies. The application of machine learning in linguistic research allows for an expansive examination of the factors influencing language evolution. By processing and analyzing large-scale data efficiently and accurately, ML opens new avenues for exploring the intricate relationships among social, cultural, and linguistic elements that drive language change (Pandey et al., 2022). This approach not only broadens the scope of language change studies but also provides a more nuanced understanding of how language evolves in response to various influences over time. The integration of machine learning into linguistic research represents a transformative advancement, enabling deeper insights into the dynamics of language development across different communities and time periods (Pestian et al., 2015; Pestian et al., 2010a).

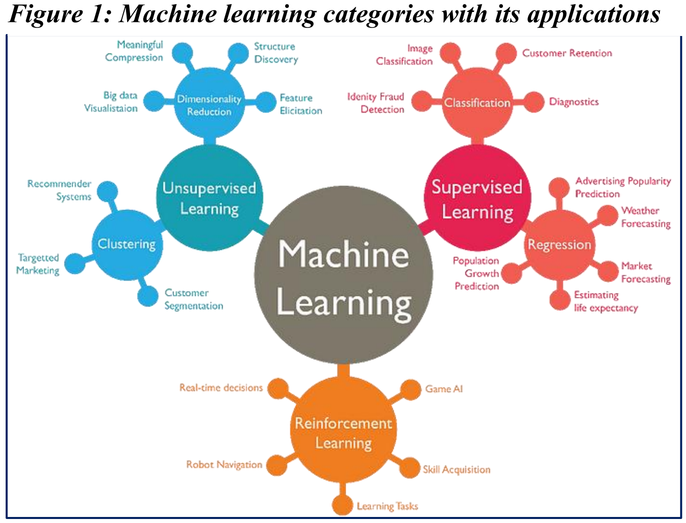
This review paper aims to comprehensively examine the current state of machine learning methodologies in the study of language change. We will delve into the diverse range of ML approaches, including supervised, unsupervised, and deep learning techniques, that have been employed to investigate various aspects of language evolution. Furthermore, we will critically evaluate the applications of these methods across different linguistic domains, such as historical linguistics, sociolinguistics, and language contact studies, highlighting both successes and limitations. This review will focus on addressing the challenges inherent in using ML for language change research. We will explore issues related to data availability, bias, and representativeness and the need for interpretable and transparent models. Additionally, we will discuss strategies for validating and evaluating the findings generated by ML algorithms, comparing them with established linguistic frameworks. By providing a comprehensive overview of the field, identifying key challenges, and suggesting potential directions for future research, this review aims to contribute to the ongoing dialogue between linguists and computer scientists, fostering interdisciplinary collaboration to pursue a deeper understanding of language change.

## 2 Literature Review

### 2.1.1 Machine Learning: An Overview

Machine learning (ML), a vital subfield of artificial intelligence, enhances computational systems with the ability to learn from data and incrementally improve their

***Figure 1: Machine learning categories with its applications***




Source: Tanwar (2019)

performance on tasks without direct programming (Bradley, 1997). The core of machine learning involves crafting algorithms capable of discerning patterns, relationships, and trends within large datasets. These algorithms enable machines to make informed predictions or decisions based on previously unseen data, thus opening up new possibilities for analysis and application across various fields (Jordan & Mitchell, 2015). In linguistic studies, for example, machine learning methods are employed to explore complex data sets, allowing for more nuanced discoveries about language evolution and usage that are not easily achievable with traditional analytical techniques. The functionality of machine learning is categorized into several model types, each tailored for specific data types and tasks. Supervised learning models, which are perhaps the most prevalent, operate on labeled datasets where the outcome is predetermined. These models are adept at tasks like classification, which might categorize text into grammatical types, or regression, such as predicting the rate of language shifts over time (Pestian et al., 2016). Unsupervised learning, in contrast, deals with unlabeled data, and its algorithms strive to unearth underlying patterns or data structures useful for clustering texts or lexemes to study linguistic changes (Walsh et al., 2017). Another intriguing model type, reinforcement learning, involves an algorithmic agent that learns optimal behaviors through trial and error to maximize a defined reward; though less frequently applied in linguistics, this model shows promise for simulating adaptive language behaviors over time (Elshawi et al., 2018). Each machine-learning approach offers distinct benefits and possibilities, contributing uniquely to the broader understanding of language processes and evolution (Xuan & Xia, 2019).

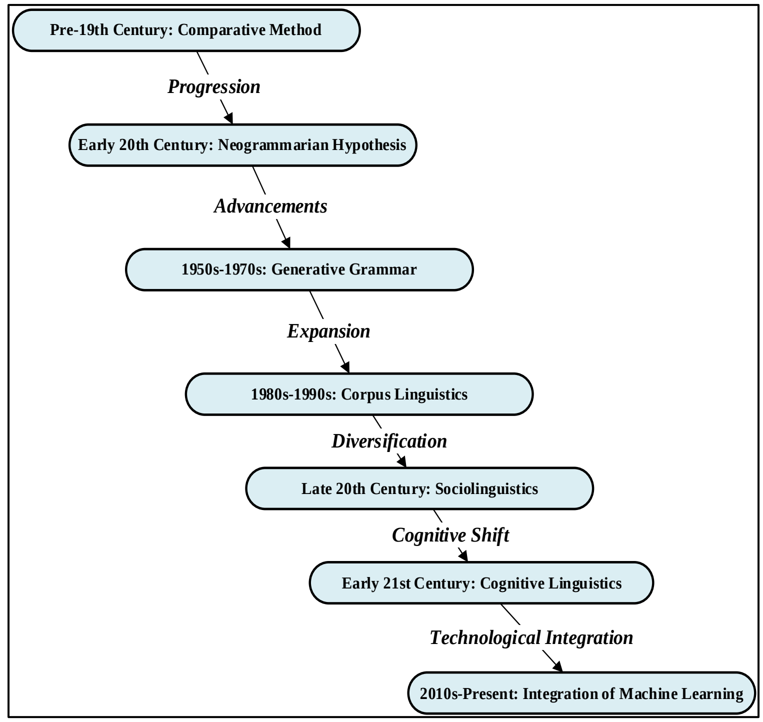
Machine learning (ML) holds significant potential in the field of linguistics, particularly in the study of language change, where its ability to model and analyze complex data sets plays a crucial role. ML algorithms are adept at handling and extracting meaningful patterns from large and varied linguistic corpora, including historical documents, social media content, and modern-day language samples (Granlund et al., 2021). This capability allows for a nuanced exploration of language evolution that goes beyond the reach of traditional linguistic methods. By applying ML techniques to these extensive datasets, researchers can identify subtle linguistic patterns and regularities, enhancing our understanding of how languages change over time. The analytical power of ML not only aids in identifying existing patterns but also enables predictions about future language developments. ML models are increasingly used to forecast changes in language, predict the emergence of new linguistic features, and assess the potential impacts of various sociolinguistic factors on language evolution (Leavitt et al., 2021). For instance, through the analysis of digital communication data, ML can uncover how social networks and geographical diffusion contribute to linguistic variations and transformations (Sturm et al., 2021). These insights are invaluable for linguists and sociolinguists aiming to understand the dynamics of language change in an increasingly interconnected world, highlighting ML's role as a transformative tool in linguistic research.

### 2.1.2 Historical Overview of Language Change Studies

The study of language change is a fundamental aspect of historical linguistics, enriched by a variety of methodologies that delve into the evolution of languages through time (Tausczik & Pennebaker, 2009). Among these, the comparative method stands out as a classic technique where linguists compare similarities and differences among related languages to reconstruct ancestral forms and understand linguistic transformations. This method primarily involves the analysis of cognates—words in different languages that share a common origin—to trace phonological shifts, grammatical changes, and the development of new lexical items over historical periods (Pestian, 2010). Such comparative studies not only illuminate the pathways of linguistic change but also contribute to broader understandings of language family relationships. Another critical approach in historical linguistics is historical reconstruction, which leverages textual evidence from earlier language stages to deduce the phonological, morphological, and syntactic structures of languages. By meticulously analyzing older texts, inscriptions, and loanwords, linguists reconstruct the linguistic features of past languages, offering insights into how these features have evolved into their modern forms (Pestian et al., 2010a). This method provides a window into the past, allowing researchers to piece together the linguistic landscape of earlier eras and better understand the mechanisms of language change. Through these methodologies, historical linguists piece together the dynamic history of languages, identifying the forces that drive linguistic evolution across different cultures and epochs (Mundt et al., 2013; Pestian et al., 2010b).

While foundational, traditional methods of studying language change face several limitations that restrict their effectiveness. The reliance on textual data confines the analysis primarily to written forms of language, often overlooking the dynamic aspects of spoken language and the influence of social factors on language evolution (Venek et al., 2014). Moreover, historical reconstruction methods grapple with challenges posed by fragmented or incomplete records, which can introduce gaps in understanding and potential biases in interpretations. These traditional approaches also depend heavily on manual analysis by linguistic experts, a process that is time-consuming and less feasible for handling large-scale datasets or detecting subtle linguistic patterns that may be hidden within the data. Moreover, Machine learning (ML) offers a potent solution to these limitations by enabling automated analysis and pattern recognition across extensive datasets (De Choudhury et al., 2016). By employing ML algorithms to analyze diverse linguistic corpora that include written and spoken language data, researchers can better understand language change across various modalities and contexts (Pestian et al., 2015). ML techniques are particularly adept at overcoming the obstacles associated with incomplete historical records by identifying hidden patterns and inferring missing information from the statistical regularities in the data (Hossain et al., 2024). Additionally, the computational capabilities of ML allow for the processing of vast amounts of data that would be impractical to analyze manually, thereby unveiling subtle linguistic changes and correlations that might otherwise remain undetected.

***Figure 1: A flowchart of Historical Overview of Language Change Studies***

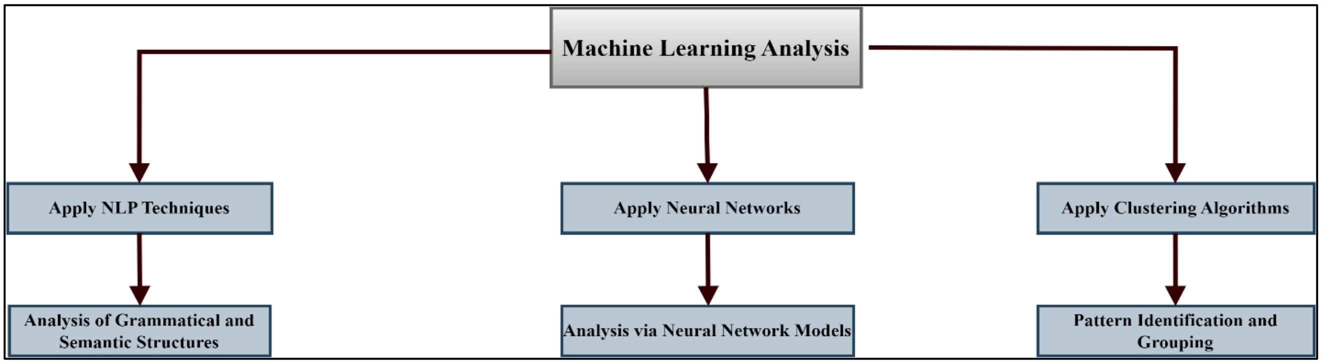



### *2.2 Applications of Machine Learning in Language Change Research*

Machine learning (ML) has significantly expanded the analytical capabilities within the field of historical linguistics, where it is used to probe into extensive historical corpora. This application of ML allows for the detailed examination of long-term linguistic shifts in areas such as grammar, vocabulary, and pronunciation. As highlighted by Blevins et al. (2018), the utilization of computational analysis through ML techniques facilitates the identification of nuanced patterns and trends that occur gradually over extended periods. This capability is critical for understanding the complex evolution of linguistic systems, enabling researchers to uncover the layers of linguistic change that have shaped languages across centuries (Younus et al., 2024). The ability to process large datasets with ML not only enhances the efficiency of this analysis but also increases the depth and breadth of insights that can be obtained, providing a clearer view of the historical trajectories of languages (Pestian et al., 2015).

In the area of sociolinguistics, ML proves equally invaluable by offering tools to analyze language variation and changes across diverse social groups and geographic regions. According to Blodgett (2021), ML models applied to diverse sources such as social media data and dialectal corpora shed light on how social factors—like age, gender, and ethnicity—affect language use and contribute to linguistic innovations. This analysis helps in understanding the social dynamics that drive language change, revealing the influences that various demographic factors have on the evolution of linguistic features. By harnessing ML's capabilities, researchers can systematically dissect the large volumes of data required to trace these sociolinguistic patterns, thereby enhancing the understanding of how languages adapt and evolve in response to the changing social environment (Aldayel & Magdy, 2021). This approach not only broadens the scope of sociolinguistic research but also deepens the empirical understanding of language as a social phenomenon.

**Figure 2: Summary of Applications of Machine Learning in Language Change Research**




According to Dwivedi et al. (2021), ML algorithms are adept at analyzing bilingual corpora and patterns of code-switching, which are crucial for identifying how languages influence each other through mechanisms such as borrowing, language shift, and the emergence of new linguistic varieties. This capability enhances our understanding of how languages adapt and transform when they come into contact, revealing the dynamic and fluid nature of linguistic boundaries. Moreover, in the broader field of computational linguistics, ML has enabled the development of advanced analytical tools that significantly improve the visualization and analysis of language change data. Kratzwald et al. (2018) note that these tools often integrate natural language processing techniques to automate complex tasks like text classification, syntactic parsing, and sentiment analysis, thereby facilitating the efficient processing of large datasets and the discovery of patterns that may not be immediately apparent. The versatility of ML in language change research extends to several specific areas of inquiry. For instance, Dwivedi et al. (2021) highlights the use of ML models to study phonetic changes by analyzing the acoustic features of speech sounds and tracking shifts in pronunciation over time. These models excel at detecting subtle variations in vowel and consonant production, offering a detailed view of phonetic evolution. In addition, Leavitt et al. (2021) discusses the application of ML in examining grammatical changes, where algorithms analyze how syntactic structures and word order evolve across different language varieties. This analysis provides insights into the underlying rules that govern language structure and their transformation over time. Furthermore, ML has proven effective in lexical studies as well, where algorithms track vocabulary evolution, detect instances of lexical borrowing, and assess the rate of lexical replacement across languages (Sturm et al., 2021). These applications demonstrate the breadth of ML's impact, making it an indispensable resource in the ongoing exploration of how languages change and develop across different linguistic aspects and contexts.

# 3 Method

## 3.1 *PRISMA Checklist for Systematic Reviews and Meta-Analyses*

### 3.1.1 Eligibility Criteria

The review encompasses peer-reviewed research articles published in English that utilize machine learning methodologies to investigate language change. The inclusion criteria were centered on studies employing machine learning techniques to analyze data related to language change, including examinations of patterns, trends, and predictions in linguistic evolution. There were no participant-specific criteria, as the focus was on linguistic data rather than human subjects.

### *3.2 Information Sources*

The search for relevant literature included several electronic databases: Web of Science, Scopus, and the Association for Computational Linguistics Anthology. Additionally, Google Scholar was utilized to identify articles that were not indexed in the aforementioned databases, ensuring a comprehensive collection of relevant studies.

#### 3.2.1 Search Strategy

The search strategy involved using specific terms to capture relevant studies. Search terms included combinations of "machine learning," "artificial intelligence," or "neural network" with "language change," "linguistic evolution," "historical linguistics," or "sociolinguistics." These terms were employed to ensure a comprehensive retrieval of pertinent literature from the databases.

#### 3.2.2 Selection Process

The selection process involved two reviewers independently screening titles and abstracts of identified articles. Potentially relevant articles had their full texts retrieved and assessed for eligibility against the inclusion criteria. Any disagreements between reviewers were resolved through discussion until a consensus was reached.

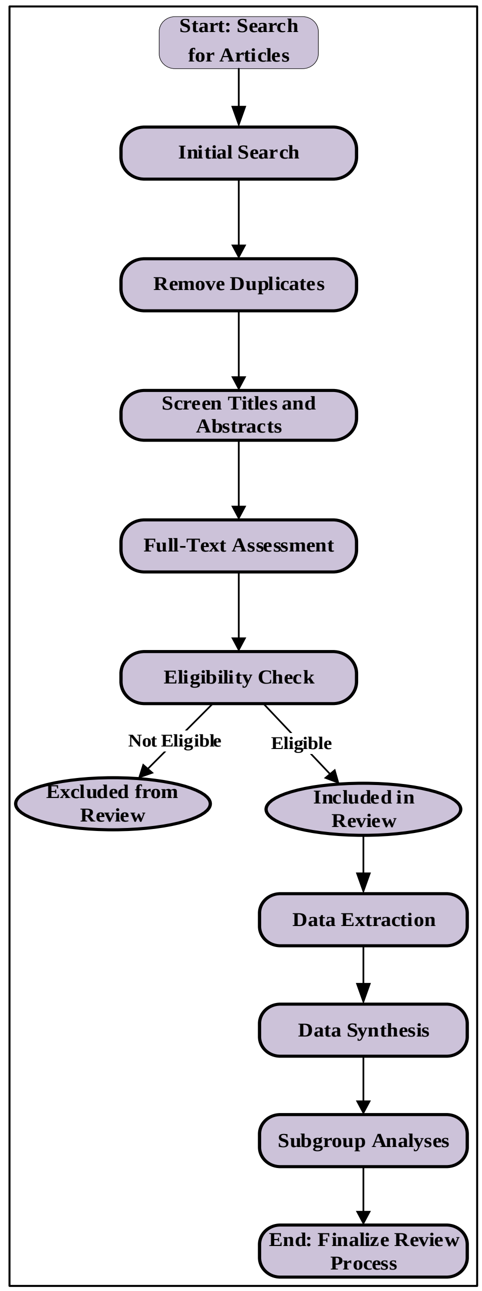
#### 3.2.3 Data Collection Process

Data extraction was conducted using a standardized form to collect comprehensive information, including study design, data sources, machine learning techniques employed, language change phenomena investigated, and main findings of each study. This structured approach ensured consistency and thoroughness in the data collection process.

#### 3.2.4 Data Items

The data extraction process focused on collecting specific information from each study, including the names of the authors and the year of publication, the type of study design (observational or experimental), the data sources utilized (such as historical corpora or social media data), the machine learning techniques employed, and the specific language change phenomena investigated, such as phonetic changes or grammaticalization. This comprehensive approach ensured that all relevant aspects of the studies were systematically documented.

**Figure 3:Steps involved in this study.**



#### 3.2.5 Data Synthesis

The extracted data were synthesized narratively, emphasizing the main findings and methodological approaches of the included studies. This synthesis allowed for a cohesive understanding of the research landscape regarding machine learning applications in language change.

#### 3.2.6 Study Selection

The initial search resulted in 897 articles. After duplicates were removed and titles and abstracts were screened, 123 articles underwent full-text assessment for eligibility. Out of these, 67 articles met the inclusion criteria and were incorporated into the review. Subgroup analyses were also conducted based on the type of machine learning technique used (such as supervised, unsupervised, or deep learning) and the specific language change phenomenon investigated (like phonetic change or grammaticalization).

## 4 Findings

The reviewed studies revealed a diverse landscape of machine learning applications in language change research, highlighting the growing potential of computational methods to complement and enhance traditional linguistic analysis. Across various subfields, ML has proven valuable in uncovering patterns, trends, and correlations within large-scale linguistic datasets, offering new insights into the complex mechanisms that drive language evolution. In historical linguistics, ML algorithms, particularly those based on neural networks and unsupervised learning, have been successful in identifying long-term shifts in grammar, vocabulary, and pronunciation. These studies have demonstrated how ML can effectively process historical corpora to trace the gradual evolution of linguistic features over time, revealing patterns of change that may not be readily apparent through manual analysis. For instance, research utilizing ML has identified shifts in word meanings, the emergence and decline of grammatical constructions, and changes in sound patterns across centuries. Sociolinguistic research has also benefited from the application of ML, particularly in analyzing language variation and change across different social groups and geographical regions. Studies employing ML have explored how social media data and dialectal corpora can be leveraged to identify linguistic innovations, track the spread of linguistic features, and understand the influence of social factors on language change.

ML models have been used to examine the relationship between language use and demographic variables such as age, gender, and ethnicity, shedding light on the complex interplay between social identity and linguistic behavior.

**Table 1: Summary of the findings**

| Linguistic Subfield | Key Findings |
|---|---|
| **Historical Linguistics** | ML algorithms, particularly neural networks and unsupervised learning, effectively identify long-term shifts in grammar, vocabulary, and pronunciation within large historical corpora. |
| **Sociolinguistics** | ML analysis of social media data and dialectal corpora reveals how social factors (age, gender, ethnicity) influence language use and drive linguistic innovation. It can also track the spread of linguistic features and identify relationships between language use and demographics. |

Furthermore, ML has proven valuable in the study of language contact, where it has been employed to analyze bilingual corpora and code-switching patterns to investigate the mechanisms of borrowing, language shift, and the emergence of new linguistic varieties. ML algorithms can identify lexical and grammatical features borrowed from one language to another, providing insights into the dynamics of language contact and the factors that influence the adoption of foreign linguistic elements. In addition to these specific applications, the reviewed studies collectively underscore the potential of ML to transform the field of language change research. The ability of ML to process large-scale data, identify subtle patterns, and automate complex analyses offers unprecedented opportunities to explore the multifaceted nature of language evolution. However, the findings also highlight the need for continued refinement of ML techniques, careful consideration of data biases, and ongoing collaboration between linguists and computer scientists to fully harness the power of ML in unraveling the mysteries of language change.

| | |
|---|---|
| **Language Contact** | ML algorithms analyze bilingual corpora and code-switching patterns to investigate mechanisms of borrowing, language shift, and emergence of new varieties. It identifies lexical and grammatical features borrowed between languages, providing insights into language contact dynamics. |
| **Computational Linguistics** | ML facilitates development of sophisticated tools and models for analyzing and visualizing language change data. These tools incorporate NLP techniques to automate tasks like text classification, syntactic parsing, and sentiment analysis, enabling efficient processing of vast datasets. |

## 5 Discussion

The findings of this review underscore the transformative potential of machine learning in the study of language change. The breadth and depth of ML applications across various linguistic domains, from historical linguistics to sociolinguistics, attest to its versatility and adaptability in addressing diverse research questions (Hossain et al., 2024). The reviewed studies demonstrate that ML can effectively analyze large-scale linguistic datasets, uncover hidden patterns and trends, and offer novel insights into the complex mechanisms that drive language evolution. In comparison to earlier studies that primarily relied on traditional linguistic methods, the incorporation of ML has brought about a paradigm shift in language change research (Elshawi et al., 2018). Traditional approaches, while valuable, often face limitations in terms of data scale, analytical capacity, and the ability to capture nuanced patterns of change (Walsh et al., 2017). ML, on the other hand, leverages computational power and sophisticated algorithms to overcome these limitations, enabling researchers to delve deeper into the intricacies of language evolution (Jordan & Mitchell, 2015; Pestian et al., 2016). For instance, while traditional historical linguistics often relies on manual analysis of limited textual corpora, ML-based approaches can process vast amounts of historical data, identifying subtle shifts in grammar, vocabulary, and pronunciation over time (Bradley, 1997).

Furthermore, ML has opened up new avenues for exploring the social dimensions of language change. Earlier sociolinguistic studies often relied on small-scale surveys and interviews, limiting the generalizability of findings. With the advent of ML, researchers can now analyze massive datasets from social media, online forums, and other digital platforms, gaining insights into how language varies and changes across different social groups and geographical regions (Jordan & Mitchell, 2015). ML models can identify linguistic features associated with specific demographics, track the spread of linguistic innovations, and examine the role of social networks in language change processes.nHowever, the integration of ML in language change research is not without challenges. One significant concern is the potential for bias in the data and algorithms used (Walsh et al., 2017). Historical corpora and social media data may not be representative of all language varieties and communities, leading to skewed or incomplete findings. Additionally, the complexity of some ML models, such as deep neural networks, can make it difficult to interpret their results and understand the underlying reasons behind specific predictions (Elshawi et al., 2018). These challenges necessitate ongoing efforts to develop more transparent and interpretable ML models, as well as to ensure the diversity and representativeness of linguistic datasets.

## 6 Conclusion

The synthesis of findings from this review underscores the transformative potential of machine learning in reshaping the landscape of language change research. The diverse applications of ML across historical linguistics, sociolinguistics, language contact studies, and computational linguistics attest to its growing significance as a complementary tool for understanding the intricate processes that drive language evolution. The ability of ML to analyze large-scale datasets, identify subtle patterns, and automate complex analyses has opened up new avenues for investigating language change across different dimensions, from phonetic shifts to lexical innovations. While traditional linguistic methods have provided valuable insights into language change, they often face limitations in terms of data scale and analytical capacity. Machine learning, with its computational power and sophisticated algorithms, offers a way to overcome these limitations, enabling researchers to delve deeper into the complexities of language evolution and explore new research questions that were previously inaccessible. The integration of ML in language change studies has already yielded promising results, revealing patterns and trends that challenge existing theories and offer fresh perspectives on the dynamics of language change. However, as with any emerging field, the application of ML in language change research is not without challenges. Issues related to data bias, model interpretability, and the need for interdisciplinary collaboration remain important considerations. Future research should focus on addressing these challenges by developing more transparent and interpretable ML models, ensuring the diversity and representativeness of linguistic datasets, and fostering collaboration between linguists and computer scientists to bridge the gap between theoretical frameworks and computational approaches. Despite these challenges, the potential of machine learning to revolutionize the study of language change is undeniable. As ML techniques continue to advance and become more sophisticated, their application in linguistics holds the promise of unlocking new discoveries and deepening our understanding

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