

COMPUTATIONAL MODELING OF LANGUAGE EVOLUTION: A STUDY OF DIACHRONIC LINGUISTICS

Dr. Nailah Riaz

Prof./HoD English Language & Literature, The University of Faisalabad,
ORCID iD <https://orcid.org/0000-0002-2054-2232>
nailah.riaz@tuf.edu.pk

Abstract

This study explores the computational modeling of language evolution in Pakistan, focusing on the diachronic changes in regional languages due to language contact, particularly the influence of Urdu. Using agent-based models, evolutionary algorithms, and network theory, the researcher simulated the transmission and evolution of linguistic features, such as phonology, morphology, and syntax, across multiple generations. The study's primary aim was to understand how language shifts occur in multilingual societies, considering both social factors and government policies. By comparing the simulation results with historical data from archival materials and contemporary language surveys, the study identified key patterns in language change, particularly the role of Urdu in reshaping regional languages. The findings offer new insights into the mechanisms of language evolution and highlight the importance of social networks and language policies in shaping linguistic outcomes.

Keywords: Computational modeling, language evolution, diachronic linguistics, Urdu, regional languages, agent-based models, network theory, language shift.

Introduction

Computational modeling of language evolution represents a powerful tool in the field of diachronic linguistics, offering insights into how languages change over time. By utilizing various computational techniques such as agent-based modeling, evolutionary algorithms, and network theory, researchers can simulate the intricate processes underlying language evolution in ways that traditional methods often cannot. This approach allows scholars to study the dynamics of language change in a controlled, repeatable environment while considering a variety of factors, including social interaction, cognitive processes, migration, and cultural shifts (Dalieva, 2024).

The Emergence of Computational Linguistics

Historically, linguistics has largely relied on qualitative methods, including the study of historical texts, oral traditions, and cross-linguistic comparisons, to understand how languages evolve. While these methods have provided deep insights, they often do not fully account for the complex, dynamic nature of language change. As computational tools became more accessible, scholars began to experiment with quantitative approaches to better model and predict linguistic changes. Computational models allow researchers to simulate multiple scenarios of language evolution by adjusting key parameters, such as population size, communication patterns, and the introduction of new linguistic features (Church & Liberman, 2021). One of the primary advantages of computational modeling is the ability to simulate complex systems. Language evolution is not merely a linear or deterministic process but involves feedback loops, chance occurrences, and unpredictable interactions among language users. Traditional linguistic studies, by relying mostly on historical data, can struggle to replicate the complexity and unpredictability of language change. Computational models, in contrast, offer a way to simulate this unpredictability, helping researchers explore how languages might evolve under different social and environmental conditions (Marin Vargas, Cominelli, Dell'Orletta, & Scilingo, 2021).

Agent-Based Models in Language Evolution

One of the most widely used computational techniques in language evolution research is agent-based modeling (ABM). In ABMs, individual "agents" (representing speakers or communities) interact according to specific rules that govern how they communicate and learn from one another. These models simulate how linguistic features spread or disappear over time, allowing researchers to observe how languages evolve at both the individual and community levels (Lipowska & Lipowski, 2022). In the context of language evolution, agents in a model can represent people who speak different languages or dialects. These agents may engage in interactions based on geographic proximity, social networks, or other factors that influence the likelihood of language contact. Through such interactions, agents can influence one another's linguistic choices, leading to changes in their speech over time. This process models how linguistic features such as pronunciation, vocabulary, and grammar may spread or change as people come into contact with different speakers (Gao et al., 2024).

Agent-based models offer several key benefits. First, they allow researchers to control and manipulate different variables, such as the rate of communication between speakers or the probability that an individual adopts a linguistic feature. This ability to experiment with different parameters can help scholars understand the dynamics of language change under various conditions. For example, researchers might explore how linguistic features spread through communities with strong social ties compared to more fragmented, isolated communities. By adjusting these factors, researchers can simulate different scenarios of language change and study the results (Grifoni, D'ulizia, & Ferri, 2021). ABMs allow for the modeling of language contact, which is a crucial factor in language evolution. In real-world scenarios, languages are often influenced by contact with other languages, whether through trade, migration, colonization, or cultural exchange. In a computational model, the researcher can simulate the effects of language contact by allowing agents to learn and borrow linguistic features from other agents who speak different languages. This can provide valuable insights into the mechanisms by which languages influence one another, contributing to phenomena like lexical borrowing, syntactic change, or even language shift and death (Liang, Luo, Hu, & Li, 2022).

Evolutionary Algorithms and Language Change

Another computational tool used to model language evolution is evolutionary algorithms (EAs). These algorithms draw inspiration from the principles of natural selection and genetic inheritance, making them particularly suitable for simulating the evolution of linguistic systems over time. In evolutionary algorithms, linguistic features are treated as "traits" that can be passed down or modified across generations of agents (Wu, Wu, Wu, Feng, & Tan, 2024). Linguistic traits are subject to selection pressures, where some features may become more prevalent within a population due to factors such as ease of use, social prestige, or the frequency of use in communication. Similarly, other traits may fade away or be replaced by newer, more advantageous forms. Just as in biological evolution, linguistic features can mutate, leading to the appearance of new forms or variations that may be subject to selection by other agents in the model. Over time, these processes of variation, selection, and inheritance can lead to the emergence of new linguistic forms and the modification or disappearance of older ones (Lanzi & Loiacono, 2023). Evolutionary algorithms can be particularly useful for studying long-term language change, especially in terms of phonological shifts, syntactic reorganization, and morphological simplification. By applying evolutionary principles, researchers can model how linguistic systems adapt to their social and

cognitive environments. For instance, they might explore how changes in pronunciation or grammar occur in response to the social dynamics of language communities, such as migration or intergenerational language transmission (Sun et al., 2022).

Evolutionary algorithms provide a way to simulate the spread of linguistic innovations across generations. This is especially important for understanding how new linguistic features arise, how they are adopted by speakers, and how they become entrenched within a speech community. For example, researchers can use evolutionary algorithms to study how a new word or grammatical construction might spread from one part of a community to another, eventually becoming a stable feature of the language (Guerrero Montero, Karjus, Smith, Blythe, & Theory, 2025). Network theory is another key component in computational modeling of language evolution. It involves analyzing how the structure of social networks can affect the spread of linguistic features. Social networks, defined as patterns of connections between individuals or groups, play a central role in language transmission. Linguists have long recognized the importance of social factors, such as prestige, social proximity, and frequency of interaction, in the spread of linguistic features. Computational models, however, allow researchers to map these relationships in a more precise and dynamic way (Fedorenko, Ivanova, & Regev, 2024). In a network-based model of language evolution, individuals are represented as nodes in a network, and the links between them represent the possibility of linguistic influence. These links can be based on various factors, such as geographic proximity, kinship, occupation, or shared social spaces. As agents interact, linguistic features can spread through the network, either gradually or rapidly, depending on the structure of the network and the social dynamics at play. Network theory thus provides a way to understand how language change might spread through a community based on who communicates with whom (Huang et al., 2025).

One of the key insights offered by network theory is the role of central nodes, or highly connected individuals, in the spread of linguistic innovations. In real-world communities, certain individuals—such as leaders, celebrities, or social influencers—may have a disproportionate impact on language change due to their prominence and their widespread social connections. By using network models, researchers can simulate how such individuals might influence the adoption of linguistic features across the community (H. Wu et al., 2024). Network models can help explain why some linguistic features spread quickly, while others remain localized or eventually disappear. Factors such as the density of connections within a network, the mobility of individuals, and the level of contact with other linguistic groups can all influence the spread of linguistic features. In regions where there is high linguistic diversity, network theory can help explain why certain languages or dialects come to dominate, while others become marginalized or even extinct (Gutiérrez & Ethics, 2024).

Applications of Computational Models to Real-World Linguistic Questions

Computational models of language evolution can be applied to a variety of real-world linguistic phenomena. One of the most compelling applications is the study of language contact, which occurs when speakers of different languages interact. In regions with high linguistic diversity, such as South Asia or Europe, the influence of one language on another can lead to significant changes in the structure and vocabulary of the affected languages. Computational models allow researchers to simulate these interactions in ways that provide new insights into how languages change in contact situations (Patwardhan, Marrone, & Sansone, 2023). For example, researchers might use computational models to explore how languages with a large number of speakers—such as English, Spanish, or Urdu—can influence smaller, minority languages. This can help explain

patterns of lexical borrowing, changes in syntax, and even the gradual shift from one language to another. These models can also shed light on how languages evolve in response to social factors like migration, urbanization, and globalization (Saleem, Bhatti, & ul Ain, 2025). Another application of computational models is the study of language shift and death. In multilingual societies, languages are often subject to shift, where speakers gradually adopt a dominant language, often due to economic, political, or social pressures. Through computational simulations, researchers can explore the factors that contribute to language shift and the rate at which it occurs under different conditions. Additionally, these models can provide insights into language revitalization efforts, helping policymakers understand how to prevent language death and promote linguistic diversity (Iannantuono et al., 2023).

Computational modeling of language evolution is a transformative approach that enriches our understanding of how languages change over time. By using tools like agent-based models, evolutionary algorithms, and network theory, researchers can simulate complex linguistic dynamics that would otherwise be difficult to study. These models offer valuable insights into the mechanisms behind language change, particularly in the context of social interaction and language contact. As computational power continues to grow, the potential for more detailed and accurate models of language evolution will likely expand, providing deeper insights into one of the most fundamental aspects of human culture—language (Liu et al., 2022).

Research Objectives

1. To develop a computational model simulating the evolution of language in Pakistan, focusing on phonological, morphological, and syntactic changes.
2. To analyze the role of social networks and migration in shaping language change in multilingual societies.
3. To assess the impact of language policies, especially the promotion of Urdu, on the evolution of regional languages in Pakistan.

Research Questions

1. How do agent-based models help simulate the diachronic evolution of regional languages in Pakistan?
2. What role do social networks play in the transmission and spread of linguistic innovations in Pakistan's diverse communities?
3. How do language policies, particularly the promotion of Urdu, influence the shift from regional languages to Urdu in different areas of Pakistan?

Significance of the Study

This study is significant for several reasons. First, it provides a novel computational approach to understanding language evolution, offering a new method of modeling linguistic changes that can be applied to multilingual contexts like Pakistan. Second, the research highlights the critical role of social factors such as community interactions, migration, and media exposure in shaping language change, which has practical implications for language planning and policy-making. Finally, the study offers valuable insights into the long-term effects of language policies, specifically the role of Urdu in influencing regional languages, which could inform future linguistic policies in Pakistan and other multilingual societies. The findings also contribute to the broader field of diachronic linguistics by advancing our understanding of how language evolves over time in complex social environments.

Literature Review

Computational modeling has become an increasingly important tool in understanding the complex and dynamic processes of language evolution. Researchers in the field of diachronic linguistics have long sought to understand how languages evolve, but traditional methods based on historical texts, cross-linguistic comparisons, and diachronic data have often been limited in their capacity to fully capture the fluid and unpredictable nature of linguistic change. Computational modeling offers a way to address this challenge by allowing researchers to simulate language evolution under various conditions, taking into account not just linguistic structures but also social, cognitive, and environmental factors that influence language change over time (Reichle, 2021). The integration of computational methods into the study of language evolution allows scholars to consider a variety of scenarios and variables that would be difficult, if not impossible, to study using conventional linguistic approaches. Among the most significant of these methods are agent-based models, evolutionary algorithms, and network models, each offering distinct advantages for simulating the mechanisms of language change. These techniques have opened new avenues for exploring questions related to the spread of linguistic features, language contact, language variation, and the emergence of new languages or dialects (Denning & Tedre, 2021). Agent-based modeling (ABM) has become one of the most widely used tools for simulating language evolution. In an ABM, agents represent individuals or communities, and these agents are programmed to interact with one another according to predefined rules. The interactions between agents can lead to the spread of linguistic features, such as words, phonemes, or syntactic structures, and the models can simulate how these features evolve or disappear over time. One of the key advantages of ABM is its ability to model the complex, decentralized processes of language transmission and change that are influenced by various social, cognitive, and environmental factors. By adjusting parameters such as the frequency of communication, the size of populations, or the strength of social networks, researchers can simulate different scenarios of language change and investigate how specific linguistic features spread through a community (Liang et al., 2022).

Through ABM, researchers can explore the social dynamics that influence language evolution, including how language features are transmitted across generations, the role of language contact, and the effects of migration and social networks on language change. For example, ABM can model how linguistic features from a dominant language might spread into a minority language due to the influence of social networks, or how certain features might be retained in isolated communities due to limited communication with outsiders. This flexibility allows researchers to investigate not only the mechanisms of language change but also how different social and cultural factors might contribute to language divergence or convergence (Fatima & Nadeem, 2025). Another computational tool that has proven useful in modeling language evolution is evolutionary algorithms (EAs). Inspired by biological evolution, EAs simulate the process of natural selection, where linguistic features (treated as traits) undergo variation, selection, and inheritance. The presence of a linguistic feature in a population can be influenced by factors such as its ease of use, its social prestige, or its communicative effectiveness. In these models, features are subject to mutation, which allows for the generation of new linguistic forms, and the frequency of features can increase or decrease over time depending on their relative advantages in communication (De Luca, Lampoltshammer, Parven, & Scholz, 2022). Evolutionary algorithms provide a robust framework for studying long-term language change, particularly in the context of phonological shifts, grammatical changes, and syntactic restructuring. By applying the principles of evolutionary theory to language, researchers can simulate how new linguistic forms emerge, how

they are selected for or against by speakers, and how they become entrenched or fade out of use. These models can also help explain how different linguistic systems adapt to changing social or cognitive environments. For example, in multilingual societies, speakers may shift from one language or dialect to another in response to social, economic, or political pressures, and EAs can model how these shifts might occur over generations, taking into account both linguistic and extralinguistic factors (Gautam & Gautam, 2021).

In addition to ABM and evolutionary algorithms, network theory has also become an important tool for understanding how language evolves within social networks. Social networks represent the patterns of interactions between individuals, and network theory can help model how linguistic features spread through these networks over time. The structure of the network—whether it is dense or sparse, centralized or decentralized—can have significant effects on how linguistic features are transmitted. For example, a small, tight-knit community may see the rapid spread of a new linguistic feature, while a more fragmented, less interconnected community may experience slower or more localized linguistic change (Bentley & Lim, 2022). Network theory also allows researchers to model the influence of key individuals within a social network, such as opinion leaders, social influencers, or individuals with high social capital. These individuals may play a disproportionate role in the spread of linguistic features, either by directly influencing others or by serving as conduits for the spread of linguistic change. Network models can also explain why certain linguistic features spread quickly, while others remain confined to specific social groups or regions. The interplay between social structure and language change is a key aspect of computational modeling, and network theory provides a useful lens for understanding these dynamics (Axtell & Farmer, 2025). The application of computational models to the study of real-world linguistic phenomena has yielded significant insights into a range of issues in diachronic linguistics. One such area is the study of language contact, which occurs when speakers of different languages interact. In multilingual regions, languages often influence one another, leading to the borrowing of words, sounds, and grammatical structures. Computational models can simulate these interactions and shed light on the mechanisms by which linguistic features are exchanged and incorporated into other languages. For example, models can explore how lexical borrowing occurs in response to cultural exchange, trade, or migration, and how these borrowed features become integrated into the grammatical structure of the recipient language (Kalter, 2022). Another area where computational modeling has proven valuable is in the study of language shift and language death. In many parts of the world, languages are undergoing rapid shifts, as smaller, minority languages are increasingly replaced by dominant global languages. Computational models can help simulate the factors that contribute to language shift, including economic, political, and social factors, and can provide insights into the processes that lead to language extinction. These models can also inform language revitalization efforts by identifying the conditions under which a language is most likely to survive and thrive in a changing social landscape (Flores Morales, Kim, Fong, & Studies, 2022).

The role of computational modeling in diachronic linguistics is particularly evident in its ability to handle the complexities of language evolution that traditional methods struggle to address. By incorporating social dynamics, cognitive processes, and environmental factors into the models, researchers are able to test hypotheses about language change in ways that would be difficult to achieve using purely qualitative methods. Furthermore, computational models allow for the replication of linguistic change across different contexts, providing a more nuanced understanding of how languages evolve in diverse settings (Kircher & Hawkey, 2022). Despite its promise, there

are still challenges and limitations to the use of computational modeling in language evolution research. The accuracy of these models depends heavily on the quality and assumptions of the underlying algorithms and the data used to calibrate them. While computational models can simulate complex scenarios, they are only as good as the parameters and assumptions built into them. As computational power increases and our understanding of linguistic processes deepens, however, these models are likely to become even more sophisticated, providing more accurate and detailed insights into the evolution of language (Dehkordi et al., 2021). Computational modeling represents a transformative approach to the study of language evolution. By using techniques such as agent-based modeling, evolutionary algorithms, and network theory, researchers are able to simulate the processes of language change in ways that were previously impossible. These models offer valuable insights into the mechanisms of language evolution, particularly in the context of social interaction, language contact, and the spread of linguistic features. As the field continues to develop, computational models will likely play an increasingly central role in shaping our understanding of the dynamic and complex nature of language evolution (Fang, Hu, & Development, 2022).

Research Methodology

The researcher employed a computational modeling approach to study language evolution in the context of diachronic linguistics in Pakistan. The study began by collecting historical linguistic data from a variety of regional languages, focusing on phonetic, morphological, and syntactic changes over time. This data was sourced from written records, oral histories, and contemporary language surveys. The researcher then developed agent-based models to simulate the evolution of language, incorporating evolutionary algorithms to track changes in linguistic features across multiple generations. These models accounted for social factors, such as community interaction and migration patterns, which were particularly relevant in Pakistan's diverse linguistic landscape. Statistical analyses were applied to evaluate the consistency and accuracy of the models, comparing simulated language changes with actual historical data. Additionally, the researcher utilized network theory to understand the spread of linguistic innovations within social groups, considering the role of social networks in language transmission. The models were tested against specific cases of language contact and shift, such as the influence of Urdu on regional languages in Pakistan. This methodology allowed the researcher to examine how language evolves dynamically in a socio-cultural context, providing valuable insights into the underlying mechanisms of linguistic change in the region.

Data Analysis

The analysis of computational models for language evolution, specifically in the context of diachronic linguistics in Pakistan, requires a multifaceted approach that incorporates both qualitative and quantitative methods. The focus of this analysis is to validate the hypotheses presented by the computational models, examining whether they accurately reflect historical linguistic changes, specifically within the unique sociolinguistic landscape of Pakistan. The researcher aimed to simulate language evolution using agent-based models, evolutionary algorithms, and network theory, allowing for the examination of various linguistic features such as phonology, morphology, syntax, and the social dynamics influencing these features. The data analysis section will explore the results of these models and compare them with the actual historical linguistic data sourced from written records, oral histories, and contemporary surveys of regional languages. It will also discuss how the models were tested against specific cases of

language contact and shift, particularly focusing on the role of Urdu in shaping other languages within the region.

Data Collection

The first step in the data analysis involved gathering extensive historical and contemporary data on the linguistic features of the selected regional languages in Pakistan, such as Punjabi, Pashto, Sindhi, Balochi, and others. The historical data was sourced from a variety of archival materials, including ancient manuscripts, historical texts, and linguistic surveys conducted in earlier decades. This data provided a basis for understanding how these languages have evolved over time, particularly in terms of phonetic, morphological, and syntactic changes. In addition to historical records, contemporary language surveys conducted in the present day were used to capture current linguistic features and any ongoing shifts in language use. Oral histories, collected through interviews and ethnographic fieldwork, were also instrumental in identifying informal language usage and transmission across generations.

The data covered a broad range of linguistic features, including phonological changes such as vowel shifts and consonant assimilation, morphological alterations like the simplification or complexification of verb conjugations, and syntactic shifts in word order and sentence structure. These elements were used to construct the input parameters for the computational models, ensuring that the models were grounded in real-world data.

Model Development

The next phase of the research involved the development of computational models, specifically agent-based models (ABMs), to simulate language evolution over time. Agent-based modeling allowed the researcher to represent linguistic features as agents interacting within a network, with each agent representing an individual or group within a linguistic community. The model was designed to simulate the transmission of linguistic features from one agent to another, considering both social and cognitive factors that affect language change. Evolutionary algorithms were incorporated to track the selection and retention of specific linguistic features across multiple generations of agents. These algorithms mimicked the process of language change in a way that reflected both individual variation and the collective patterns observed in real-world language communities.

To create a more accurate simulation, the researcher accounted for several sociolinguistic variables, such as community size, social status, and the level of language contact. In Pakistan, the influence of Urdu as a national language and its widespread use in education, media, and government created a significant source of language contact with regional languages. This was modeled by introducing interactions between Urdu-speaking agents and agents speaking other regional languages. By adjusting parameters such as the frequency of interactions and the degree of influence exerted by Urdu on these regional languages, the model could simulate the potential outcomes of language shift and convergence over time.

Analysis of Results

Once the computational models were implemented, the next step was to analyze the results in relation to the historical and contemporary data collected. The primary goal of this analysis was to evaluate how well the model's predictions aligned with the actual linguistic changes observed in the historical and contemporary data. This process involved a series of statistical comparisons and qualitative evaluations to determine the accuracy of the simulations.

One of the key metrics used in this analysis was the rate of linguistic change, specifically in terms of the phonological, morphological, and syntactic features modeled. For example, the simulation

tracked how the vowel shifts in Punjabi or the simplification of verb conjugations in Pashto compared with historical data on these changes. The model's ability to replicate these shifts was measured by comparing the simulated linguistic data with actual data from written texts and contemporary surveys. The accuracy of the model was assessed through the calculation of correlation coefficients between the predicted and observed rates of linguistic change. A high degree of correlation would indicate that the model successfully replicated real-world language evolution.

Additionally, the researcher examined the role of social networks in language change. By utilizing network theory, the researcher was able to simulate the spread of linguistic innovations through social connections. In Pakistan, social networks play a critical role in the transmission of linguistic features, with factors such as geographic location, community size, and migration patterns influencing how language evolves. The model allowed for the analysis of how language changes spread within different social groups, and whether these changes followed the patterns seen in historical and contemporary data. For example, the influence of Urdu on regional languages was modeled through the establishment of links between Urdu-speaking agents and agents from various regional language communities. The analysis focused on how quickly and to what extent Urdu linguistic features (such as vocabulary and grammar) were adopted by speakers of regional languages.

One specific case tested was the spread of Urdu's vocabulary into Punjabi, Pashto, and Sindhi. These languages have long been in contact with Urdu, particularly due to urbanization, migration, and the role of Urdu in education and the media. The model simulated the rate at which regional language speakers incorporated Urdu words into their vocabulary and how this influence affected the overall linguistic landscape. The results of this simulation were compared with historical records and contemporary surveys that documented the degree of lexical borrowing from Urdu.

Another important aspect of the analysis was the examination of language shift and maintenance. The models provided insights into how language shift, particularly from regional languages to Urdu, might have occurred over time. Factors such as social prestige, economic opportunities, and government policies (such as the promotion of Urdu in education and the media) were incorporated into the simulation. The researcher compared these simulated shifts with actual patterns of language maintenance and loss, as observed in the historical and contemporary data. For example, in urban areas where Urdu has been the dominant language, the simulation predicted a stronger shift away from regional languages. In contrast, in rural or less urbanized areas, the model suggested a slower rate of language change, as seen in the maintenance of regional languages like Sindhi and Pashto in certain communities.

Statistical Validation

To assess the robustness of the computational models, the researcher applied a series of statistical tests to validate the accuracy of the simulations. One of the primary methods of validation was cross-validation, in which the model's predictions were compared with independent datasets not used in the training phase. This allowed for an objective evaluation of the model's ability to generalize to new data.

The researcher also employed regression analysis to evaluate the relationship between different sociolinguistic factors and the rate of language change. For instance, regression models were used to determine the impact of social factors such as migration, education, and media exposure on the rate of language shift. These analyses helped identify the key factors influencing linguistic

evolution in Pakistan and provided a deeper understanding of the processes driving language change in the region.

Additionally, the researcher used chi-square tests to examine the distribution of linguistic features across different social groups. This statistical test was used to evaluate whether certain linguistic features, such as the adoption of Urdu vocabulary, were significantly more common in specific social or geographical groups. The results of these tests provided further insights into the social dynamics of language change and the factors that promote or hinder linguistic convergence.

Interpretation of Findings

The findings from the computational models were consistent with several key patterns observed in the real-world linguistic data. First, the models confirmed that language change in Pakistan follows a non-linear trajectory, with periods of rapid change followed by phases of stabilization. This aligns with historical data showing periods of linguistic convergence, especially in areas with high levels of Urdu speakers, followed by periods of resistance to linguistic shift in more rural areas.

The models also highlighted the role of social networks in shaping the spread of linguistic innovations. In urban centers, where Urdu was more dominant, the rate of language shift was higher, with speakers of regional languages incorporating a greater number of Urdu words and grammatical structures. In contrast, in rural areas, where regional languages were more entrenched, the model suggested a slower rate of change, consistent with the observed linguistic maintenance in these areas.

Furthermore, the simulation of language shift provided valuable insights into the long-term effects of language policies. The model showed that government policies promoting Urdu in education and the media significantly accelerated the shift away from regional languages. This finding supports the hypothesis that language policies, especially those favoring a national language, can exert a powerful influence on linguistic evolution.

Summary of Data Analysis

The data analysis of the computational modeling of language evolution in Pakistan confirmed the viability of using agent-based models and evolutionary algorithms to simulate diachronic linguistic changes. The results showed that the models were able to replicate key patterns of linguistic evolution, such as phonological, morphological, and syntactic shifts, as well as the role of social networks and language contact in driving these changes. By comparing the simulated data with historical and contemporary linguistic data, the researcher was able to gain valuable insights into the processes driving language change in Pakistan. The findings also demonstrated the importance of social, cognitive, and environmental factors in shaping the trajectory of language evolution, offering new perspectives on the dynamics of linguistic change in a multilingual society.

Conclusion

The computational modeling of language evolution in Pakistan provided valuable insights into the complex dynamics of diachronic linguistic change. Through the use of agent-based models, evolutionary algorithms, and network theory, the researcher was able to simulate the processes of language shift, convergence, and maintenance within the context of Pakistan's diverse sociolinguistic landscape. The results demonstrated that language change in the region follows a non-linear trajectory, with periods of rapid linguistic shift followed by stabilization, particularly in areas where Urdu exerts significant influence over regional languages. The study highlighted the role of social networks and social factors such as migration, education, and media exposure in shaping language evolution. Additionally, the findings confirmed the substantial impact of

government language policies on language shift, underscoring the significance of promoting or limiting the use of certain languages in shaping linguistic outcomes. By validating the computational models with real-world data, the researcher was able to enhance the understanding of the processes driving language evolution in multilingual societies like Pakistan.

Recommendations

The findings of this study suggest several directions for future research and policy-making. First, further exploration of the role of social networks in language change is recommended, particularly in rural communities where the influence of Urdu may be more gradual. Future studies could consider how other regional languages, such as Pashto or Balochi, are affected by urbanization and the spread of digital media. Additionally, policymakers could benefit from using computational models to predict the outcomes of different language policies in Pakistan, particularly in light of the rising influence of English in education and governance. Researchers should also focus on the role of digital communication and social media in accelerating language contact and change, as these factors were not fully captured in the current study.

References

- Axtell, R. L., & Farmer, J. D. J. J. o. E. L. (2025). Agent-based modeling in economics and finance: Past, present, and future. *63(1)*, 197-287.
- Bentley, P. J., & Lim, S. L. J. W. I. R. C. S. (2022). From evolutionary ecosystem simulations to computational models of human behavior. *13(6)*, e1622.
- Church, K., & Liberman, M. J. F. i. A. I. (2021). The future of computational linguistics: On beyond alchemy. *4*, 625341.
- Dalieva, M. J. W. o. T. I. R. (2024). DIACHRONIC CORPORA AND LANGUAGE EVOLUTION OVER TIME. *2(10)*, 58-60.
- De Luca, G., Lampoltshammer, T. J., Parven, S., & Scholz, J. J. S. S. (2022). A literature review on the usage of agent-based modelling to study policies for managing international migration. *11(8)*, 356.
- Dehkordi, M. A. E., Ghorbani, A., Bravo, G., Farjam, M., van Weeren, R., Forsman, A., . . . Simulation, S. (2021). Long-term dynamics of institutions: Using ABM as a complementary tool to support theory development in historical studies. *24(4)*, 7.
- Denning, P. J., & Tedre, M. J. I. i. E. (2021). Computational thinking: A disciplinary perspective. *20(3)*, 361.
- Fang, F., Hu, G. J. J. o. M., & Development, M. (2022). English medium instruction, identity construction and negotiation of Teochew-speaking learners of English. 1-16.
- Fatima, S., & Nadeem, M. U. J. F. i. P. (2025). Family language policy and heritage language transmission in Pakistan—the intersection of family dynamics, ethnic identity and cultural practices on language proficiency and maintenance. *16*, 1560755.
- Fedorenko, E., Ivanova, A. A., & Regev, T. I. J. N. R. N. (2024). The language network as a natural kind within the broader landscape of the human brain. *25(5)*, 289-312.
- Flores Morales, J., Kim, J., Fong, E. J. J. o. E., & Studies, M. (2022). Peer effects on the educational outcomes of immigrant youth: heterogeneity by generation and school context. *48(17)*, 4166-4190.
- Gao, C., Lan, X., Li, N., Yuan, Y., Ding, J., Zhou, Z., . . . Communications, S. S. (2024). Large language models empowered agent-based modeling and simulation: A survey and perspectives. *11(1)*, 1-24.

- Gautam, B. L., & Gautam, B. L. (2021). *Language Contact in Nepal*: Springer.
- Grifoni, P., D'ulizia, A., & Ferri, F. J. I. A. (2021). When language evolution meets multimodality: Current status and challenges toward multimodal computational models. *9*, 35196-35206.
- Guerrero Montero, J., Karjus, A., Smith, K., Blythe, R. A. J. C. L., & Theory, L. (2025). Reliable detection and quantification of selective forces in language change. *21(1)*, 31-73.
- Gutiérrez, J. L. M. J. A., & Ethics. (2024). On actor-network theory and algorithms: ChatGPT and the new power relationships in the age of AI. *4(4)*, 1071-1084.
- Huang, X., Wen, Y., Zhang, F., Li, H., Sui, Z., & Cheng, X. J. O. E. (2025). Accident analysis of waterway dangerous goods transport: Building an evolution network with text knowledge extraction. *318*, 120176.
- Iannantuono, G. M., Bracken-Clarke, D., Floudas, C. S., Roselli, M., Gulley, J. L., & Karzai, F. J. F. i. O. (2023). Applications of large language models in cancer care: current evidence and future perspectives. *13*, 1268915.
- Kalter, F. (2022). Integration in migration societies. In *Handbook of sociological science* (pp. 135-153): Edward Elgar Publishing.
- Kircher, R., & Hawkey, J. J. R. m. i. l. a. (2022). 21 Mixed-Methods Approaches to the Study of Language Attitudes. 330.
- Lanzi, P. L., & Loiacono, D. (2023). *Chatgpt and other large language models as evolutionary engines for online interactive collaborative game design*. Paper presented at the Proceedings of the Genetic and Evolutionary Computation Conference.
- Liang, X., Luo, L., Hu, S., & Li, Y. J. K.-B. S. (2022). Mapping the knowledge frontiers and evolution of decision making based on agent-based modeling. *250*, 108982.
- Lipowska, D., & Lipowski, A. J. L. (2022). Emergence and evolution of language in multi-agent systems. *272*, 103331.
- Liu, R., Wei, J., Gu, S. S., Wu, T.-Y., Vosoughi, S., Cui, C., . . . Dai, A. M. J. a. p. a. (2022). Mind's eye: Grounded language model reasoning through simulation.
- Marin Vargas, A., Cominelli, L., Dell'Orletta, F., & Scilingo, E. P. J. F. i. C. S. (2021). Verbal communication in robotics: A study on salient terms, research fields and trends in the last decades based on a computational linguistic analysis. *2*, 591164.
- Patwardhan, N., Marrone, S., & Sansone, C. J. I. (2023). Transformers in the real world: A survey on nlp applications. *14(4)*, 242.
- Reichle, E. D. (2021). *Computational models of reading: A handbook*: Oxford University Press.
- Saleem, S., Bhatti, Z. I., & ul Ain, N. J. T. C. R. o. S. S. S. (2025). Pragmatics and Sentiment Analysis: Using AI to Document Cultural Variations in Pakistani Languages. *3(1)*, 1549-1560.
- Sun, X., Yue, L., Yu, L., Shao, H., Peng, X., Zhou, K., . . . Qi, H. J. J. A. F. M. (2022). Machine learning-evolutionary algorithm enabled design for 4D-printed active composite structures. *32(10)*, 2109805.
- Wu, H., Li, S., Gao, Y., Weng, J., Ding, G. J. E., & Technologies, I. (2024). Natural language processing in educational research: The evolution of research topics. 1-27.
- Wu, X., Wu, S.-h., Wu, J., Feng, L., & Tan, K. C. J. I. T. o. E. C. (2024). Evolutionary computation in the era of large language model: Survey and roadmap.