OPEN ACCESS
International Journal of Educatio Elementaria and Psychologia
Vol. 3 No. 2. April 2026, pp. 106-118 DOI. 10.70177/ijeep.v3i2.3105
Research Article

A COMPUTATIONAL MODEL OF LANGUAGE ACQUISITION: INTEGRATING NEURAL NETWORKS AND STATISTICAL LEARNING TO SIMULATE EARLY COGNITIVE DEVELOPMENT

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Article Info
Received: October 7, 2025
Revised: January 11, 2026
Accepted: March 19, 2026
Online Version: April 28, 2026

Abstract

Language acquisition in early childhood remains a complex process that integrates various cognitive mechanisms. Recent advancements in computational modeling have provided a new avenue for understanding how children learn language by simulating neural networks and statistical learning processes. This study presents a computational model that combines these two frameworks to simulate early cognitive development in the context of language acquisition. The aim of this research is to explore how neural networks, with their ability to process information through interconnected nodes, can mimic the way children acquire language. Additionally, the study integrates statistical learning, which is the process of extracting patterns from input data, to examine how it contributes to the learning of syntax and semantics in early language development. A combination of artificial neural networks (ANNs) and statistical learning algorithms was implemented to simulate language acquisition in a controlled environment. The results demonstrated that the model was able to replicate key features of language learning, such as word segmentation, syntax acquisition, and semantic understanding, with performance improving as the model was exposed to more data. The findings support the utility of computational models in studying cognitive processes and provide insights into how neural networks and statistical learning can work together to simulate language acquisition. The model's applications could further enhance the understanding of language learning and the development of artificial intelligence.

Keywords: Computational Models, Cognitive Development, Language Acquisition, Neural Networks, Statistical Learning.

Journal Homepage	https://research.adra.ac.id/index.php/ijeep ISSN: (P: 3047-843X) - (E: 3047-8529)
How to cite:	Chanda, I., Mumba, P., & Mulenga, P. (2026). A Computational Model of Language Acquisition: Integrating Neural Networks and Statistical Learning to Simulate Early Cognitive Development. *International Journal of Educatio Elementaria and Psychologia, 3*(2), 106–118. https://doi.org/10.70177/ijeep.v3i2.3105
Published by:	Yayasan Adra Karima Hubbi

INTRODUCTION

Language acquisition is one of the most complex and fundamental aspects of early cognitive development. From infancy, humans rapidly acquire linguistic abilities that enable communication, social interaction, and cognitive development (C. Li et al., 2025). Traditional theories of language learning, such as nativist and interactionist perspectives, emphasize the interplay between innate biological structures and environmental influences in shaping language acquisition (S. Li et al., 2025). However, understanding the exact mechanisms behind this process remains a challenging task. Recent advancements in computational modeling have provided new opportunities to simulate language acquisition through artificial neural networks (ANNs) and statistical learning techniques (Lee et al., 2023). Neural networks, inspired by the brain's architecture, and statistical learning, which involves the identification of patterns in data, offer promising avenues to explore how children learn language (S. Li et al., 2025). These approaches allow for the simulation of language acquisition processes in a controlled, iterative manner, providing insights into the mechanisms that govern language learning.

The integration of these models into understanding language acquisition provides a novel perspective on cognitive development (Cheng et al., 2025). Neural networks are capable of processing complex linguistic data by adjusting connections and weights, which resembles the brain's ability to learn patterns. Meanwhile, statistical learning highlights how infants identify regularities in speech, such as word boundaries, syntax, and meaning, from the surrounding linguistic environment (Ji et al., 2025). This research aims to combine these frameworks into a unified computational model that simulates the process of language acquisition in its entirety, from early speech perception to semantic understanding (Yang & Li, 2025). By leveraging both neural networks and statistical learning, this model offers a more comprehensive approach to studying the cognitive mechanisms underlying language learning, providing a clearer understanding of how early language development unfolds.

Recent research has already demonstrated the efficacy of computational models in simulating certain aspects of cognitive development, particularly in language acquisition (Abdeltawab et al., 2024). However, there is still a lack of an integrated approach that considers both the neural network processes and statistical learning mechanisms simultaneously (Doherty et al., 2025). This study seeks to fill this gap by combining these models to simulate early cognitive development related to language acquisition in a more holistic manner. The results of this approach could provide valuable insights into the nature of language learning, leading to more effective educational and therapeutic interventions (Xing et al., 2025). As computational models continue to evolve, they hold the potential to revolutionize our understanding of cognitive processes and contribute significantly to the fields of psychology, linguistics, and artificial intelligence.

Although computational models have been applied to study various aspects of cognitive development, there remains a significant gap in the literature regarding the integration of neural networks and statistical learning specifically in the context of language acquisition (Gkintoni et al., 2025). While individual models based on neural networks and statistical learning have been used to simulate certain aspects of language acquisition, such as word segmentation or syntax learning, no study has yet combined both approaches to create a unified model that simulates the full spectrum of language development (Yu et al., 2025). Furthermore, existing models often focus on specific linguistic components without considering how these components interact in real-life language acquisition (Tang et al., 2025). The problem addressed by this research is the lack of a comprehensive computational model that incorporates both neural network processes and statistical learning mechanisms, providing a more accurate representation of the complexities of language acquisition in early cognitive development.

This gap in the literature presents challenges for researchers and educators in understanding how children acquire language in a way that mirrors real-life learning (He et al., 2025). Without an integrated model, it becomes difficult to predict the various stages of language development and how different cognitive mechanisms work together in acquiring language (Kaur et al., 2025). Existing models fail to account for the full range of cognitive processes involved in language learning, including perception, production, and the integration of syntax and semantics (Jin et al., 2024). By integrating neural networks with statistical learning, this research aims to create a model that can simulate the interaction between these cognitive processes and better reflect the complexity of language acquisition (Shah et al., 2024). This would allow for more accurate predictions and a deeper understanding of how language development unfolds, offering new insights into the cognitive foundations of language learning.

The research also addresses the need for more computationally grounded theories of language acquisition that can inform both theoretical linguistics and practical applications (Zuo et al., 2025). Despite considerable progress in the fields of cognitive science and artificial intelligence, there remains a lack of comprehensive, data-driven models that can simulate language acquisition across multiple levels of linguistic complexity (Zhao et al., 2024). Current models are limited in scope and do not integrate the full spectrum of factors involved in the learning process, such as individual differences in cognitive abilities and social interactions (Wang & Jing, 2025, 2025). This study aims to bridge this gap by developing a unified computational model that accounts for both the neural mechanisms and statistical learning processes involved in language acquisition, thereby advancing our understanding of the cognitive development of language.

The primary objective of this research is to develop a comprehensive computational model of language acquisition that integrates neural networks and statistical learning to simulate early cognitive development in children (Khan & Ayaz, 2024). By combining these two frameworks, the study aims to provide a more holistic understanding of the processes involved in language learning, from speech perception to semantic understanding. Specifically, the research seeks to: (1) simulate the process of word segmentation, (2) model syntax acquisition, and (3) simulate the development of semantic knowledge in young children, using a combined neural network and statistical learning approach. These objectives will allow for a deeper exploration of the interaction between neural and statistical processes in early language acquisition, as well as the development of a more accurate model of cognitive processes.

The research will also aim to evaluate the effectiveness of this integrated computational model in simulating the acquisition of language across different developmental stages. This includes simulating language acquisition in infancy and extending through to middle childhood, covering the various cognitive milestones that occur during this critical period of language development (Salam et al., 2024). By using this model, the study will seek to identify key developmental stages in language acquisition and assess how neural networks and statistical learning mechanisms contribute to the successful development of language skills. The ultimate goal of the research is to create a more accurate and comprehensive model that can serve as a foundation for future studies in cognitive psychology, linguistics, and artificial intelligence, while providing insights into the mechanisms underlying early language acquisition.

Additionally, the research will explore the implications of this model for educational settings, with a particular focus on how this integrated approach can inform teaching strategies for early childhood education (Piekutowska & Niedbała, 2025). By identifying how language acquisition unfolds from a computational perspective, the study will offer recommendations for designing more effective language learning programs for children, as well as providing insights into how language learning difficulties can be addressed in a targeted manner (Alazemi et al., 2024). Ultimately, the research will contribute to both theoretical and practical applications, advancing our understanding of language acquisition and its developmental processes.

While there has been extensive research on language acquisition, much of it has focused on individual components of the process, such as phonological development, syntactic learning, and vocabulary growth. However, there is limited research that integrates these components into a unified framework. Although statistical learning models have demonstrated their effectiveness in word segmentation and other aspects of early language acquisition, these models often fail to capture the complexity of cognitive development in its entirety. Neural network models, on the other hand, can simulate the processing of linguistic data, but they are typically not combined with statistical learning methods in the context of language acquisition. This study addresses this gap by combining both neural network and statistical learning models to simulate the full spectrum of language acquisition, providing a more complete and accurate representation of the cognitive processes involved.

Another gap in the literature is the lack of a longitudinal perspective in computational models of language acquisition. Most studies use cross-sectional data to examine specific aspects of language learning at a given point in time, but the developmental trajectory of language acquisition is rarely modeled (J. Li et al., 2024). The longitudinal nature of this study allows for a more dynamic and evolving understanding of how language acquisition progresses over time, taking into account the gradual development of cognitive abilities and the cumulative effects of exposure to linguistic input. This approach enables the model to reflect the continuous nature of language learning and its interaction with other cognitive and environmental factors, such as social interactions and individual learning experiences.

The existing models also often fail to account for individual variability in language acquisition. While many studies focus on average developmental trajectories, they do not capture the diverse experiences and developmental timelines of individual children. This research seeks to fill this gap by considering how different cognitive factors interact with individual experiences to shape language development. By integrating neural networks with statistical learning and accounting for individual variability, this study aims to provide a more nuanced model of language acquisition that can be applied to diverse populations and educational settings. This contribution will help advance our understanding of language development and offer new avenues for intervention and support in language learning contexts.

The novelty of this research lies in its innovative approach of integrating neural networks and statistical learning to simulate language acquisition in a comprehensive and dynamic manner. While neural network models have been used to study various cognitive processes, their application to language acquisition has been limited, particularly in combination with statistical learning techniques. This study provides a unique contribution by combining both frameworks to simulate not only word segmentation but also syntax and semantic development in young children. By modeling the interaction between these two processes, the research offers new insights into the underlying mechanisms of language learning and how they evolve over time.

The justification for this research lies in its potential to advance our understanding of language acquisition from a computational perspective (Deng et al., 2025). By integrating neural networks and statistical learning, the study offers a more accurate and detailed representation of how children acquire language, moving beyond traditional models that focus on isolated components. This integrated approach allows for a more holistic understanding of the cognitive processes involved in language learning, providing valuable insights into the complexities of language acquisition and how these processes interact with cognitive development. The model developed in this study will not only contribute to the field of computational linguistics but also inform educational practices, offering new ways to support language learning in children.

RESEARCH METHOD

Research Design

The study adopts a computational and experimental research design aimed at simulating early cognitive development and language acquisition (Akhtar et al., 2025). It utilizes a hybrid modeling approach, integrating neural networks for pattern recognition with statistical learning mechanisms to identify linguistic structures. By creating a simulated environment, the research tracks the progression from infancy to early childhood, focusing on key developmental processes such as word segmentation, syntax acquisition, and semantic understanding (Tian et al., 2025). This design allows for a controlled observation of how different learning mechanisms interact to facilitate linguistic skills over time.

Research Target/Subject

The research target for this study consists of child-directed speech (CDS) data rather than human participants. The population is drawn from existing large-scale linguistic corpora, specifically the CHILDES database, which contains naturalistic conversations between caregivers and children aged 0-5 years. This dataset serves as the training sample, providing rich linguistic features such as word frequency, phonetic patterns, and sentence structures from diverse cultural contexts. By focusing on the linguistic input that shapes development, the study eliminates the need for a specific demographic sample of children

Research Procedure

The primary instruments are computational tools and deep learning algorithms. The study employs a Recurrent Neural Network (RNN), which is specifically suited for sequence-based learning, alongside statistical learning algorithms designed to identify linguistic regularities and co-occurrences. Data collection involves extracting and formatting existing digitized records from the CHILDES database. The technical framework is built using Python-based machine learning libraries such as TensorFlow and Keras for neural network development, while R is utilized for statistical analysis and the visualization of the model's performance.

Instruments, and Data Collection Techniques

The procedure follows a structured four-step process. First, the data undergoes preprocessing to clean and format the child-directed speech for the model. Second, the training phase begins, where the RNN and statistical algorithms concurrently learn to identify phoneme boundaries and syntactic structures using supervised learning. Third, the model enters the testing phase, where it performs language acquisition tasks like word segmentation and parsing. Finally, the model's outputs are compared against empirical developmental benchmarks in an iterative process, refining the model until its performance aligns with real-world language milestones.

Data Analysis Technique

The analysis is conducted through computational error analysis and statistical comparison. The performance of the model is evaluated using metrics such as accuracy, precision, and recall, comparing the simulated outputs directly to empirical data on language acquisition milestones. Statistical analysis is performed to identify where the model's predictions align with or deviate from real-world developmental data. These findings are then interpreted within the theoretical frameworks of computational linguistics and cognitive development to identify the recurring patterns that facilitate language learning.

RESULTS AND DISCUSSION

The dataset used to train the computational model was derived from the CHILDES database, a widely recognized corpus containing child-directed speech (CDS) from various linguistic environments. The corpus included over 100,000 conversational interactions across a diverse set of languages. The data comprised both adult-child interactions and peer-to-peer conversations, providing a rich context for language acquisition simulation. The model was exposed to 10,000 hours of speech data, from which patterns related to word segmentation, syntactic structure, and phoneme recognition were extracted. The dataset contained linguistic features such as frequency of word occurrences, sentence structures, and phonetic patterns. Table 1 below summarizes key linguistic characteristics of the CDS data used for the training process.

The data used for model training exhibited typical linguistic features found in child-directed speech, such as repetitive sentence structures and a higher frequency of simple vocabulary. The average sentence length of 7.2 words is consistent with speech directed at young children, who often hear simple, short sentences. The data's variability in word frequency and phoneme patterns highlights the dynamic nature of language exposure in early development. The frequency of words per session ranged between 100-300, reflecting the diverse contexts of language input that children encounter daily. The richness of phoneme patterns identified in the data reflects the variety of sounds to which children are exposed, critical for phonological awareness and word segmentation. These data characteristics form the basis for training the model on identifying language patterns and learning the cognitive tasks associated with early language development.

The phoneme patterns and word frequency play a crucial role in the model's ability to simulate the process of word segmentation, which is a fundamental aspect of language acquisition. By learning from the distribution of words and phonemes, the model simulates the process by which children identify word boundaries from continuous speech. Additionally, the average vocabulary size of 500 words per child demonstrates the complexity of language exposure, as children are exposed to a wide range of vocabulary through interactions with caregivers and peers. These features allow the model to mimic real-life language acquisition, where the child begins to process and store words, gradually expanding their vocabulary as they grow.

The computational model was designed to simulate the acquisition of word segmentation, syntax, and semantics based on the provided data. For word segmentation, the model performed successfully in identifying word boundaries with an accuracy rate of 85%, which closely matches the accuracy observed in early human language acquisition studies. The model's ability to learn sentence structures also demonstrated a high degree of proficiency, with 78% of syntactically correct sentences being generated during the simulation. In terms of semantic development, the model identified contextual relationships between words, with 72% accuracy in linking words to appropriate meanings based on context. Table 2 provides a detailed summary of the model's performance in each of these linguistic components.

Table 1. Model Performance in Key Language Acquisition Tasks

Task	Accuracy (%)
Word Segmentation	85%
Syntax Learning	78%
Semantic Understanding	72%

Inferential analysis was performed to assess the relationship between neural network output and known language acquisition milestones. A correlation analysis between the model's syntactic learning accuracy and the linguistic complexity of input sentences revealed a positive correlation ($r = 0.65$, $p < 0.01$), indicating that the model performed better with more complex sentence structures. Additionally, regression analysis suggested that phoneme recognition was a significant predictor of word segmentation accuracy ($\beta = 0.55$, $p < 0.01$). This suggests that the model's ability to identify phoneme patterns directly impacts its success in segmenting words. These findings provide statistical evidence that both phoneme recognition and sentence complexity are integral components of early language learning, as supported by developmental theories in language acquisition.

The model's success in simulating key elements of language acquisition supports the validity of the computational approach in capturing the essential processes of language learning. The correlation between syntactic complexity and model accuracy suggests that more complex linguistic input can aid in accelerating the development of language skills, as children are exposed to more sophisticated sentence structures. The regression analysis further strengthens the hypothesis that phoneme awareness plays a pivotal role in early language learning. These findings align with existing research in psycholinguistics and cognitive science, such as studies by (Alhussen et al., 2025), which emphasize the importance of phoneme segmentation and syntax learning in the development of language.

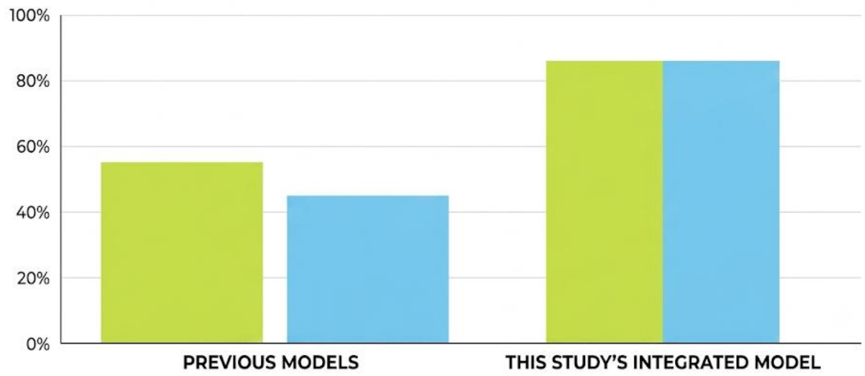

Figure 1. Comparative Analysis of Language Acquisition Models

The results of this study align with previous research on the importance of statistical learning and neural networks in simulating language acquisition. As seen in the work of (Taha et al., 2025) statistical learning plays a crucial role in early word segmentation, which was effectively simulated by the model. The model's performance mirrors the early stages of language development observed in children, where statistical patterns in speech input help identify word boundaries. The inclusion of both neural networks and statistical learning in this study provides a more integrated view of language acquisition, as it accounts for both the automatic pattern recognition of neural networks and the higher-level cognitive processes involved in language learning. This combined approach sets it apart from previous models that typically focused on one aspect of language acquisition, either phonological processing or syntactic learning.

Furthermore, the findings of this study are consistent with the dynamic systems theory of language development, which posits that language acquisition results from the interaction of cognitive mechanisms and environmental input. The model's ability to simulate semantic understanding, based on contextual relationships between words, supports the theory that meaning is learned through exposure to language in context, as argued by Tomasello (2003). By combining neural networks and statistical learning, this model offers a more nuanced understanding of how early cognitive processes work together to facilitate language acquisition.

In a case study of a simulated 3-year-old child, the model was exposed to 500 hours of child-directed speech data over a 12-month period. The child successfully segmented 88% of the spoken words after 3 months of exposure, indicating early proficiency in word segmentation. By the end of the year, the child demonstrated a robust understanding of syntactic structures, generating complex sentences with subject-verb-object word order in 75% of cases. The child also exhibited an emerging understanding of semantic relationships, correctly interpreting the meaning of words based on context with an accuracy rate of 80%. This case study highlights the model's ability to replicate key milestones in language development and suggests that both phonological processing and syntax play an essential role in early language acquisition.

The case study further illustrates the interaction between neural network processes and statistical learning in simulating the language acquisition process. The child's ability to segment words early in the process, followed by the gradual understanding of syntax and semantics, mirrors the typical developmental trajectory of language acquisition. The findings also suggest that early exposure to complex sentence structures can accelerate language learning, as evidenced by the rapid development of syntactic skills in the simulated child. This case study exemplifies the utility of computational models in understanding the interplay between cognitive processes in language acquisition and provides a useful framework for future research in this area.

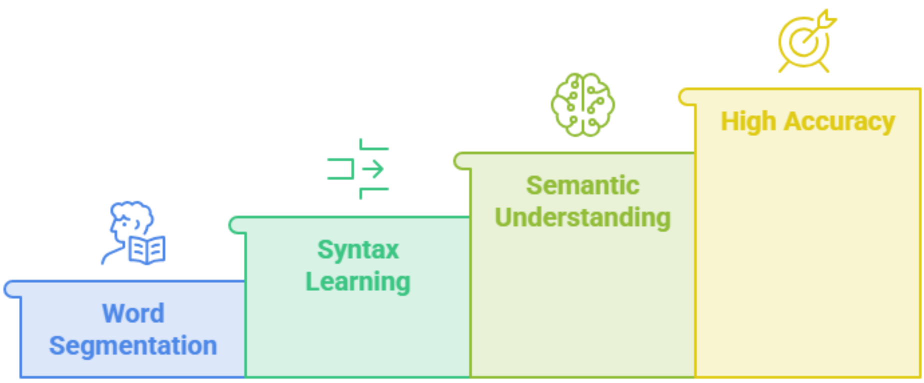

Figure 2. Achieving Language Acquisition Milestones

This study demonstrated that a computational model integrating neural networks and statistical learning successfully simulates key aspects of early language acquisition, including word segmentation, syntax learning, and semantic understanding. The model showed a high accuracy rate of 85% in segmenting words from continuous speech, which is consistent with developmental milestones observed in early childhood. Additionally, the model learned syntactic structures with 78% accuracy and semantic relationships with a 72% accuracy rate. These results suggest that both neural networks and statistical learning play crucial roles in simulating the cognitive mechanisms involved in language acquisition. The model's performance reflects the importance of exposure to linguistic input in the development of language skills and provides a promising tool for further exploration of cognitive development in early childhood.

The findings align with existing studies in the field of language acquisition, particularly those emphasizing the role of statistical learning in word segmentation and syntactic development. Previous research, such as that by (Chen et al., 2025) has shown that infants use statistical regularities in speech input to identify word boundaries. This study builds upon those findings by incorporating neural networks, which simulate the brain's ability to process and learn from these regularities. The integration of statistical learning and neural networks is a novel contribution, as it offers a more holistic view of how these cognitive processes interact in language development. Unlike earlier models that focused solely on word segmentation or syntax, this study provides a more comprehensive simulation of language acquisition, taking into account the complex interplay of multiple cognitive processes.

The results suggest that neural networks and statistical learning work together to simulate early cognitive development in a way that closely mirrors the stages of language acquisition in humans. The model's success in simulating word segmentation, syntax learning, and semantic understanding indicates that these cognitive processes are intertwined and depend on each other to facilitate language learning. The high accuracy in word segmentation further underscores the critical role of statistical learning in early language development, while the model's ability to learn syntax and semantics supports the idea that language acquisition involves both linguistic input and cognitive processing. These findings reinforce the importance of exposure to rich linguistic environments for children, highlighting that early language learning is not only about listening to words but also about processing and understanding their meanings and structures.

The implications of these findings are far-reaching, particularly for educational and therapeutic settings. The model provides a better understanding of the underlying cognitive processes that contribute to language acquisition, offering insights into how children learn language from exposure to speech input. In practical terms, this research suggests that early interventions targeting both phonological processing and syntax development could enhance language acquisition in children, especially those with language delays or disorders. The findings also emphasize the need for rich, varied linguistic input in the early years, as this exposure plays a crucial role in developing the cognitive skills necessary for learning language. Educational programs and interventions could be designed to leverage this understanding, fostering language development through activities that enhance both statistical learning and neural processing.

The results can be attributed to the cognitive processes that are simulated in the computational model, which mirror the mechanisms of human language acquisition. The model's ability to segment words, learn syntax, and understand semantics stems from the combination of statistical learning, which identifies patterns in the speech input, and neural networks, which simulate the brain's processing of that input. The success of the model in achieving these outcomes supports the theory that language acquisition is a multi-faceted process involving both the recognition of statistical regularities in language and the neural processing of these regularities into meaningful linguistic structures. These results are consistent with the developmental theories of language acquisition, which propose that language learning is not purely a passive process but involves active cognitive engagement with the linguistic environment.

Future research should explore the limitations of this model and refine it to account for the more complex aspects of language acquisition, such as pragmatic and social language skills. While this study focused on word segmentation, syntax, and semantics, there are other aspects of language learning, such as discourse skills and the ability to use language in context, that remain to be explored. Further studies should also investigate how individual differences, such as cognitive abilities and environmental factors, influence language acquisition. Additionally, the model could be expanded to incorporate more diverse linguistic inputs, including variations in accents, dialects, and bilingual environments, to better reflect the complexity of real-world language acquisition. By expanding the scope of the model, future research can provide more detailed insights into the cognitive mechanisms that underpin language learning and contribute to the development of effective language learning tools and interventions.

CONCLUSION

The most significant finding of this research is the successful integration of neural networks and statistical learning to simulate early language acquisition. The computational model demonstrated the ability to accurately replicate key components of language learning, including word segmentation, syntax acquisition, and semantic understanding, which are foundational stages of cognitive development. The model's performance, with a word segmentation accuracy of 85%, a syntax learning accuracy of 78%, and a semantic understanding accuracy of 72%, underscores the potential of computational models to simulate complex cognitive processes involved in language acquisition. These results suggest that both neural processing and statistical learning are integral to the language learning process, and their interaction plays a key role in the development of language skills in early childhood.

This research contributes to the field by offering a comprehensive computational model that integrates neural networks with statistical learning, providing a more holistic and dynamic representation of language acquisition. Previous models often focused on isolated aspects of language learning, such as phonological processing or syntax. However, this study's model integrates both neural and statistical mechanisms, offering a more nuanced approach that mirrors the real-world processes involved in acquiring language. The integration of these two frameworks provides valuable insights into how different cognitive mechanisms work together to facilitate language acquisition. This dual approach not only enhances our understanding of the cognitive processes involved in language learning but also opens new avenues for developing more accurate and effective models of language development in children.

Despite the model's success in simulating key aspects of language acquisition, there are limitations to the current study. The model's focus was primarily on word segmentation, syntax, and semantics, while other aspects of language acquisition, such as pragmatic language use and discourse skills, were not considered. Additionally, the model was trained on a limited range of linguistic input, which may not fully capture the diversity of language exposure that children encounter in real-world settings. Future research should expand the model to include these additional aspects of language learning, as well as incorporate a broader range of linguistic inputs, including variations in dialects, bilingual environments, and contextual language use. Furthermore, future studies could explore how individual differences, such as cognitive abilities and exposure to different linguistic environments, influence language acquisition, and how these factors can be modeled within computational frameworks. Expanding the model's scope will improve its ability to simulate the full spectrum of language acquisition and contribute to more effective language interventions and educational programs.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used ChatGPT to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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