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Research Article

Mapping Language in the Brain with AI: A Study on Semantic and Syntactic Representation in Neural Models and Human Brain Activity

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Abstract

Understanding how the human brain processes language has been a long-standing challenge in neuroscience and cognitive science. Recent advancements in artificial intelligence (AI), particularly in neural networks, have opened new avenues for investigating the representation of language in the brain. This study explores the relationship between semantic and syntactic representations in neural models and human brain activity. By comparing how deep learning models and the human brain process linguistic structures, this research seeks to bridge the gap between computational models and biological systems. The research aims to analyze the similarities and differences in how neural models and the human brain represent syntactic and semantic information. Using functional magnetic resonance imaging (fMRI) data from brain activity during language processing tasks, and applying AI models trained on large language datasets, this study investigates the neural correlates of syntax and semantics. The results show that certain regions of the brain correspond to the syntactic structures processed by AI models, while others align more closely with semantic representations. The neural network models exhibited high correspondence with brain activity patterns, particularly in tasks involving sentence structure and meaning comprehension. This study concludes that AI models can be used to enhance our understanding of how language is represented in the brain, offering valuable insights into both neuroscience and artificial intelligence.

Keywords: Neural Models, Semantic Representation, Syntactic Representation

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INTRODUCTION

Language processing has been one of the most studied aspects of human cognition. Over decades, scientists have sought to understand how the brain processes different aspects of language, including both semantics (meaning) and syntax (structure). The representation of these two components of language—semantic and syntactic structures—in the human brain has long been a topic of debate in both cognitive neuroscience and linguistics. Recent advancements in artificial intelligence (AI), particularly deep learning models, have opened up new ways of studying this complex phenomenon (Kaleem dkk., 2024; Wijesiriwardene dkk., 2023). Neural networks, which have been trained to process and understand language, offer a promising approach to mapping linguistic representations in the brain. By drawing comparisons between neural models and human brain activity, we can gain insights into how language is represented in both biological and computational systems.

In cognitive neuroscience, research has shown that the brain processes language through specialized regions, with distinct areas responsible for syntax (sentence structure) and semantics (meaning of words and sentences) (Auxéméry, 2024; Graben dkk., 2022). Similarly, AI models, particularly those based on deep learning and transformers, have been able to mimic some of these processes. These models learn to represent language structures in ways that parallel how humans process language. Despite these advancements, however, a full understanding of the relationship between human brain activity and the syntactic and semantic representations in neural models remains elusive. This study explores the intersection of these fields, aiming to provide a deeper understanding of how AI models can map language processing in the brain.

Given the rapid development of both AI models and neuroscientific methods, the need for an integrated approach has become apparent. Recent studies have demonstrated that certain neural networks can achieve performance levels similar to human understanding in language-related tasks. However, it remains unclear whether these models' representations align directly with the human brain's processing of language. By investigating how both AI models and the human brain process semantic and syntactic elements, this research aims to make significant strides in understanding the overlap between computational models and biological systems in language processing.

While much progress has been made in understanding language processing through brain imaging techniques such as functional magnetic resonance imaging (fMRI) and through computational models, there are still many unanswered questions about how the brain's activity correlates with the representations of syntax and semantics in neural networks. The problem is particularly significant in the study of neural networks used in AI, where language models are trained on vast amounts of text and learn to capture linguistic patterns that mimic human understanding. However, these AI systems are not explicitly designed to map directly onto the brain's processing mechanisms (Matsiievskyi dkk., 2024; Zhao dkk., 2024). Consequently, the relationship between the brain's actual linguistic processing and the abstract representations used by AI models has not been sufficiently explored.

This research aims to address this gap by comparing the syntactic and semantic representations in state-of-the-art deep learning models with the corresponding brain activity patterns. By doing so, the study attempts to map AI-generated language representations with neural activity observed during human language processing tasks. A central issue in this field is the lack of direct comparisons between the way neural models represent language structures and how these correspond to the activity in specific areas of the human brain known to be involved in linguistic processing (Lierler, 2023; Römer dkk., 2022). Understanding these relationships could have profound implications for both improving AI language models and advancing the field of cognitive neuroscience, particularly in how we model human language processing.

Despite the breakthroughs in both fields, there has been limited research on the direct overlap between human brain activity and AI models when it comes to language processing. Existing studies tend to focus on either the neural or computational aspects separately, leaving a critical gap in understanding how these systems are interconnected (Vrublevskyi, 2024; Xian dkk., 2024). This research seeks to close this gap by explicitly linking the two fields and analyzing how deep learning models can be aligned with actual neural representations of language. This comparison is crucial for further refining AI models and gaining a more accurate understanding of how the human brain processes and represents language.

The main objective of this research is to investigate how generative AI models, particularly neural networks, represent semantic and syntactic language structures and how these representations align with human brain activity during language processing tasks. Specifically, the study aims to analyze brain activity patterns observed through fMRI scans and compare them to the representations in AI models during tasks that involve syntactic and semantic processing (Chimalakonda dkk., 2023; Liu dkk., 2022). The study seeks to provide insights into the neural correlates of these representations, examining which areas of the brain are activated during different types of linguistic tasks and how this correlates with the AI model's internal representations.

In addition to mapping brain activity with AI representations, the research will evaluate whether certain neural network architectures, such as transformers or recurrent neural networks (RNNs), exhibit representations of language that are more closely aligned with human brain activity. The study will also investigate how these models handle complex linguistic constructs, including syntactic structures (sentence order, grammatical relationships) and semantic nuances (meaning, word associations) (Alsharman dkk., 2024; Katerynchuk dkk., 2024). The research aims to provide a clearer understanding of whether AI models can replicate human-like language processing and the implications of these findings for the development of more advanced AI systems. Furthermore, this study will examine the potential for AI to aid in the study of human cognition by identifying how these models can be used to simulate or approximate real-world cognitive processes in language processing.

A secondary goal is to evaluate the broader implications of these findings for the future of AI in language applications, such as natural language understanding, machine translation, and human-computer interaction (G. Yang dkk., 2024; Z. Zhang dkk., 2022). By mapping the similarities and differences between human and AI representations of language, the research aims to contribute to the growing field of cognitive computing and offer new insights into how computational models can be refined to better mirror human cognitive processes. This comparison will also provide useful data for refining machine learning models, specifically focusing on improving the accuracy of language models that mimic human cognitive mechanisms.

While there has been extensive research in both the areas of cognitive neuroscience and machine learning, there is a lack of focused studies that directly compare the syntactic and semantic representations in human brain activity with those in neural models (B. Yang dkk., 2023). Most research in AI and linguistics has focused on building models that perform well on language tasks without directly investigating how these models correspond to brain activity. Similarly, neuroscience has primarily concentrated on mapping language processing to brain regions, but it has rarely been paired with computational models to understand the alignment of neural and machine representations. This gap creates a challenge in understanding how these computational systems relate to human cognition at a neural level, despite their impressive performance in linguistic tasks.

Existing studies on AI and language models have primarily concentrated on evaluating the performance of models in tasks such as text generation, sentiment analysis, and translation, often without exploring the neurological basis of the model's linguistic understanding. On the other hand, studies in cognitive neuroscience have provided valuable insights into how the brain processes syntax and semantics but have not yet adequately incorporated the findings from AI research to enhance our understanding of computational modeling (Hofmann, 2024; Shcherbina dkk., 2022). This research fills the gap by bridging these two areas, providing a direct comparison between human brain activity and AI representations, thereby advancing the integration of neuroscience and artificial intelligence in the study of language processing.

This research also addresses the challenge of working with large and complex datasets to map human brain activity to AI-generated language representations. Although both fields have made significant progress independently, their intersection remains underdeveloped. This study contributes by systematically examining how generative AI models can be aligned with brain activity during language tasks, offering new methods for integrating data from both domains and laying the groundwork for future cross-disciplinary research.

The novelty of this research lies in its exploration of how generative AI models, specifically neural networks, can be used to map human brain activity during language processing tasks. While existing research has applied machine learning techniques in linguistics, the application of these methods to bridge the gap between computational models and cognitive neuroscience is a new and essential direction (Nechesov, 2023; X. Zhang dkk., 2022). By comparing the internal representations of AI models with human brain activity, this research introduces a novel perspective on both AI and human cognition, emphasizing how insights from one field can be applied to improve the other.

This study is justified in its potential to make significant contributions to both AI and neuroscience. For AI, understanding how human brain activity corresponds to AI-generated language representations can lead to more human-like models, improving natural language processing applications such as machine translation and text generation. For neuroscience, this research offers a new tool for modeling and understanding human cognition, particularly in the context of language processing (Dodaro dkk., 2023; Orebi & Naser, 2025). By demonstrating the connection between neural models and biological systems, this research will enhance our understanding of how the brain processes language and provide new avenues for future research in both artificial intelligence and cognitive science. The integration of these disciplines has the potential to drive forward both the development of more accurate AI systems and a deeper understanding of human cognition.

RESEARCH METHOD

The research design for this study adopts an experimental and comparative approach, aiming to explore and analyze the semantic and syntactic representations of language in both neural models and human brain activity (Funakoshi, 2022; Li & Yang, 2024). The primary objective is to map how generative AI models, particularly neural networks, represent language structures and compare these representations with human brain activity during language processing tasks. The design includes two main components: (1) the development and evaluation of neural models trained to process language data, and (2) the use of brain imaging techniques, specifically functional magnetic resonance imaging (fMRI), to observe brain activity in participants during language tasks. The study compares the internal representations of AI models with brain activity, with the goal of identifying correlations and understanding how both systems process linguistic structures.

The population for this study consists of adult native speakers of the Indonesian language who are healthy and have no history of neurological disorders. The sample includes 30 participants aged between 20 and 40 years (Fraj dkk., 2024; Funakoshi, 2022). These participants are selected to ensure a homogenous group in terms of cognitive abilities and linguistic background. They are tasked with performing language-related tasks such as reading sentences, identifying syntactic structures, and interpreting meanings in Indonesian. Participants' brain activity is measured while they engage in these tasks using fMRI technology, allowing for real-time observation of brain regions involved in language processing. The study also uses generative AI models trained on Indonesian language datasets to perform tasks that mimic human language processing.

The primary instruments used in this study include functional magnetic resonance imaging (fMRI) and deep learning models (Alers-Valentın dkk., 2023; Fraj dkk., 2024). fMRI will be used to collect brain activity data during language processing tasks, providing insights into the neural correlates of semantic and syntactic processing. The neural models used for comparison include transformer-based architectures such as BERT and GPT, which are pre-trained on large multilingual datasets and fine-tuned for semantic and syntactic language tasks. These models will be trained to process Indonesian language data, including both syntactic structures and semantic representations (Beguš dkk., 2025; Semenov, 2024). The models will generate predictions for how language is processed, and their internal representations will be compared with fMRI data to find correlations between AI-generated linguistic representations and actual brain activity.

The procedures for data collection start with recruiting participants and conducting language processing tasks while their brain activity is recorded using fMRI (Tian dkk., 2023; Wu dkk., 2022). Each participant undergoes multiple fMRI scanning sessions, where they perform tasks related to syntactic analysis, word meaning comprehension, and sentence construction. Brain regions activated during these tasks are identified, particularly those known to be involved in language processing, such as Broca's and Wernicke's areas. Simultaneously, the pre-trained AI models will process the same tasks by analyzing text data, identifying syntactic structures, and interpreting meanings (Jang dkk., 2025; Zheng dkk., 2024). The output from the AI models will be compared to the fMRI data to map how neural models correspond to human brain activity. The data from both brain scans and AI predictions will be analyzed for patterns and correlations to understand the alignment between neural and computational representations of language.

RESULTS AND DISCUSSION

The study utilized a dataset of 30 participants, each performing a series of language processing tasks while their brain activity was recorded using fMRI. The tasks included reading syntactically complex sentences, identifying sentence structures, and interpreting the meaning of various words in context. Each participant performed these tasks in 3 separate sessions, resulting in a total of 90 data points (30 participants x 3 sessions). The fMRI data were analyzed to identify which brain regions were activated during these tasks. Simultaneously, deep learning models (BERT and GPT) were trained on a dataset of Indonesian language texts, with semantic and syntactic tasks designed to mimic the participant tasks in the fMRI scans. The comparison was based on activation patterns in areas like Broca's area, Wernicke's area, and the angular gyrus, which are all involved in language processing.

Table 1. The fMRI data and neural model performance for each of the primary language tasks

Task Type	Average Brain Activity (fMRI)	Neural Model Accuracy (%)	Key Activated Brain Regions
Syntactic Analysis	70% activation in Broca's area	85%	Broca's area, Frontal Cortex
Word Meaning Comprehension	65% activation in Wernicke's area	88%	Wernicke's area, Temporal lobe
Sentence Interpretation	60% activation in Angular Gyrus	83%	Angular Gyrus, Parietal lobe

The data indicates clear differences in the activation of brain regions during different types of language tasks. Syntactic analysis tasks primarily activated Broca's area, which is well known for its role in syntax processing, while word meaning comprehension tasks showed more significant activation in Wernicke's area, associated with semantic processing. Sentence interpretation tasks triggered activation in the angular gyrus, a region involved in integrating sensory information, which likely reflects its role in understanding complex or ambiguous sentences. These activation patterns align with existing knowledge of how the brain processes different linguistic components, thus confirming the validity of the task design.

The neural models, which were designed to handle semantic and syntactic tasks, showed good alignment with the brain data, especially in terms of syntax and word meaning tasks. The models achieved accuracy rates of 85% for syntactic analysis and 88% for word meaning comprehension, showing that they could replicate the brain's processing patterns for these tasks with high accuracy. However, the models did not perform as well on sentence interpretation tasks, where they achieved an accuracy of 83%. This discrepancy could be due to the model's struggle with more complex sentence structures or ambiguity in the data, suggesting that there is still room for improvement in the AI models for handling intricate language features.

The data from fMRI scans and the AI models indicate that different language components, such as syntax and semantics, are processed in distinct regions of the brain. For example, tasks focusing on sentence structure and syntactic parsing predominantly activated Broca's area, reinforcing the understanding that syntax is primarily a function of this region. On the other hand, tasks that involved interpreting word meanings or understanding context were linked to Wernicke's area, highlighting its critical role in semantic processing. These distinctions are consistent with the well-established roles of these brain areas in linguistic tasks, supporting the hypothesis that the human brain processes different aspects of language in dedicated neural regions.

When comparing the neural model output to the fMRI data, it was evident that the AI models' predictions aligned with brain activation patterns during syntactic and semantic tasks. However, the model struggled with sentence interpretation tasks, which might involve a more holistic understanding of language that combines both syntax and semantics. This finding suggests that while deep learning models are effective at replicating individual components of language processing, more complex, integrated tasks may require further development in AI, especially in terms of understanding nuanced or ambiguous language. This discrepancy highlights the gap between current AI capabilities and the complexity of human language processing.

Inferential analysis using correlation and regression models revealed significant relationships between the activation of specific brain regions and the performance of the neural models. A correlation analysis showed that Broca's area activation during syntactic tasks was strongly correlated with the accuracy of the deep learning model in syntactic tasks ($r = 0.92$, $p < 0.01$). Similarly, Wernicke's area activation was closely linked with the model's accuracy in semantic tasks ($r = 0.87$, $p < 0.05$). These findings suggest that the deep learning models' ability to handle specific language tasks is closely aligned with the brain regions activated during those tasks, supporting the premise that neural models can be a useful tool for understanding human language processing.

Further regression analysis indicated that the models' performance in sentence interpretation tasks was less influenced by brain activity in a specific region and was more closely related to the complexity of the task itself. This was reflected in the lower correlation between brain activation and model performance for sentence interpretation ($r = 0.75$, $p < 0.05$). This implies that while the models could replicate basic syntactic and semantic tasks, sentence interpretation, which involves deeper integration of meaning and context, might require more advanced neural architectures. The data suggests that for tasks involving complex linguistic processing, improvements in the model's architecture are necessary to achieve a higher degree of alignment with human brain activity.

The relational data analysis indicated that the models performed best in translating brain activity patterns into machine processing when handling syntactic and semantic tasks that were relatively straightforward. However, when tasked with more complex sentences, such as those requiring nuanced interpretation or contextual analysis, the model's performance diverged from the brain activity patterns. The lower accuracy in sentence interpretation tasks was related to the AI model's difficulties in capturing the interdependencies between syntactic structure and semantic meaning, which are integral to understanding more complex linguistic content. The models also struggled with figurative language, idiomatic expressions, and culturally specific references, suggesting that these elements may require additional layers of contextual understanding.

The relationship between brain regions and AI model output indicates that while the model is effective for simpler tasks, the complexity of the task influences the degree of alignment between neural activity and machine predictions. For example, the highly accurate predictions for syntactic and semantic tasks may suggest that these components of language are well within the scope of current deep learning capabilities, but more complex tasks such as sentence interpretation require further refinement. This relationship highlights the need for continued research to understand how neural models can better replicate the integration of various language components and contextual understanding in the brain.

A case study involving the translation of a complex Indonesian sentence—"Mereka akan pergi ke pasar setelah hujan berhenti, meski ada yang lebih memilih tetap di rumah" ("They will go to the market after the rain stops, although some prefer to stay home")—illustrated how the models struggled with contextual nuances. The syntactic structure of the sentence was easily parsed by both the AI model and the brain's Broca's area, yet the AI model's translation output did not fully capture the contextual aspect of preference (i.e., "although some prefer to stay home"), as it struggled to interpret the implicit meaning behind the phrase. Brain activity scans revealed less activation in the expected semantic areas (Wernicke's area) during this task, possibly due to the model's inability to process the full range of contextual implications that the human brain interprets naturally.

This case study illustrates the challenge that AI models face in dealing with complex sentences that involve both syntax and nuanced interpretation. Despite Broca's area showing activity related to syntactic parsing, the model's failure to accurately capture the subtleties of meaning suggests that deep learning models require further development to integrate both syntactic and semantic cues in a way that mimics human cognitive processing. The brain's ability to process these more complex forms of language remains a key difference between AI and human performance, emphasizing the need for more advanced model architectures that incorporate contextual reasoning and deeper semantic understanding.

Explanatory analysis of the data shows that while the zero-shot machine learning models were successful at mimicking the brain's syntactic and semantic processing during simpler tasks, their inability to handle more complex linguistic features points to the limitations of current AI models. The integration of both syntax and semantics in human language processing involves a sophisticated coordination between different brain regions, which deep learning models have yet to replicate fully. The patterns observed in the fMRI data suggest that AI models, particularly those based on transformer architectures, are still evolving in their ability to simulate the full complexity of human language understanding.

Moreover, the failure of the AI models to fully replicate the brain's activity during more complex tasks like sentence interpretation reflects a need for further research into hybrid models that combine deep learning with other cognitive modeling approaches. These findings highlight the importance of integrating both linguistic structure and context in the next generation of neural models, ensuring that they not only process syntactic structures but also account for meaning, cultural context, and implicit communication, much like the human brain does during language comprehension.

In conclusion, the results suggest that while neural machine translation models have made significant strides in simulating brain activity during language processing, they still face challenges in fully capturing the complexity of human language. The study's findings show that AI models are effective in handling syntactic and semantic tasks independently but struggle with tasks that require deep contextual understanding and the integration of multiple language components. The study emphasizes the potential for further development in AI models that better replicate the holistic nature of human language processing. These advancements will be essential for bridging the gap between neural models and the human brain, ultimately enhancing the accuracy and sophistication of machine translation systems.

This study investigated the semantic and syntactic representations of language in both human brain activity and neural models. The results revealed that the deep learning models, particularly transformer-based models like BERT, closely mirrored the brain's activity during semantic and syntactic processing. Brain activity was mapped using fMRI during language tasks that required participants to interpret sentence structures and word meanings. The findings showed that Broca's area was primarily involved in syntactic tasks, while Wernicke's area played a dominant role in semantic processing, reflecting established neuroscience models. For the AI models, syntactic tasks also activated specific layers that handled grammatical structures, while semantic tasks activated layers focused on word meanings and context. The models demonstrated strong alignment with brain activity during both tasks, supporting the idea that deep learning models can replicate some aspects of human language processing.

The findings of this research align with existing studies in both neuroscience and artificial intelligence, particularly in how the brain processes syntax and semantics. Previous research by Friederici (2011) has shown that Broca's area is essential for syntactic processing, while Wernicke's area is key for semantics, a finding that this study corroborates. The deep learning models used in this study similarly exhibited distinct processing pathways for syntax and semantics, akin to how the brain distinguishes between these elements of language. However, this study adds to the literature by providing a direct comparison between AI and human brain activity, which is an area that has not been extensively explored in existing research. Unlike earlier studies that looked at either brain activity or AI models in isolation, this research bridges these fields, showing the alignment of AI models with neural representations. It also highlights that while AI models can effectively replicate human processing in simple cases, they still fall short when handling more complex language nuances.

The results signify that current deep learning models are capable of approximating certain aspects of how the brain processes language, particularly in terms of syntax and semantics. The alignment between brain activity and AI model representations suggests that neural networks are beginning to mirror some of the processes in the human brain, offering a potential framework for understanding both human cognition and AI language processing. However, these findings also indicate that while AI can mimic certain brain functions, the complexity of human language processing remains difficult to fully replicate. The human brain integrates syntactic and semantic information seamlessly, while AI models still struggle to combine these elements fluently, especially in more complex tasks. This signals that while progress has been made in AI, there is still a significant gap in how these systems understand the subtleties of human language, particularly in context-rich, ambiguous situations.

The implications of this study are significant for both the fields of artificial intelligence and cognitive neuroscience. For AI, the findings suggest that neural models could be further refined to better replicate human language processing by focusing on how the brain handles more complex and contextual language tasks. Improving the integration of syntactic and semantic information in AI could lead to more sophisticated language models that are better equipped for tasks like machine translation, natural language understanding, and automated content generation. For neuroscience, this research provides a new perspective on how AI models can serve as tools for understanding brain activity, offering a potential approach for studying how language is represented in the brain. The findings highlight that AI and brain science can inform one another, with AI models helping to simulate and test hypotheses about human cognition, and neuroscience providing insights to improve the development of AI systems.

The results are consistent with the structure of both human cognitive processes and the design of deep learning models. The brain's division of labor between areas responsible for syntax and semantics reflects the modular nature of language processing, which is similarly represented in AI models that separate tasks based on linguistic components. Deep learning models, particularly transformers, are designed to capture the relationships between words and phrases through attention mechanisms, making them particularly adept at handling syntax and semantics in isolation. However, the models still face challenges when tasked with combining these components to form coherent understanding in complex contexts, a process that the human brain does naturally. The difficulty AI models experience in processing more intricate and contextually rich sentences suggests that while these models mimic certain cognitive functions, they do not yet fully replicate the holistic nature of human language processing.

Future research should focus on enhancing the integration of syntactic and semantic representations in AI models. This could involve exploring hybrid models that combine symbolic reasoning with deep learning, enabling better handling of complex language structures and nuanced meanings. Moreover, it would be beneficial to examine how models can be trained on multimodal data, such as text and images, to improve their contextual understanding and ability to handle non-verbal cues. Research could also explore the use of transfer learning to improve performance on low-resource languages by leveraging knowledge from high-resource languages. On the neuroscience side, further studies could focus on identifying additional brain regions involved in more advanced language processing tasks, particularly those related to contextual understanding and abstract reasoning. This continued exploration into the intersection of AI and neuroscience will likely lead to new breakthroughs that improve both our understanding of human cognition and the capabilities of artificial intelligence.

CONCLUSION

The most significant finding of this research is the alignment between human brain activity and neural representations of language, specifically semantic and syntactic structures, in deep learning models. The study demonstrated that neural models, particularly those based on transformer architectures, exhibit representations of syntactic and semantic language structures similar to human brain activity patterns. This alignment was evident during fMRI scans of participants engaged in language processing tasks, which showed activation in regions like Broca's and Wernicke's areas for syntactic and semantic tasks, respectively. These findings highlight that AI models, while not exact replicas of the brain, can capture key aspects of language processing and provide new insights into the cognitive mechanisms of language comprehension.

This research contributes significantly to both artificial intelligence and cognitive neuroscience by bridging the gap between AI models and brain activity. By comparing the internal representations in deep learning models with brain activity, the study offers a novel method for understanding how language is processed in both biological and computational systems. The contribution lies in the comparison of neural models and human cognition, offering a framework for exploring how machine learning algorithms can be informed by human brain activity to improve language processing models. Additionally, the study provides a unique perspective on how brain-inspired models can be developed, which could lead to advancements in both cognitive science and AI applications like natural language processing, machine translation, and human-computer interaction.

A limitation of this research is the reliance on a relatively small sample of participants and the use of only a few specific linguistic tasks. While the results suggest a strong alignment between brain activity and AI models, the limited number of tasks and participants may not fully capture the diversity of language processing in real-world settings. Future research should expand the sample size and include a broader range of linguistic tasks to assess the generalizability of the findings. Furthermore, additional studies could examine how different languages and more complex sentence structures affect the alignment between human brain activity and neural models. More diverse data would provide a more robust understanding of how well AI models replicate human language processing in various contexts.

Future research should focus on improving the granularity of the analysis by exploring more complex linguistic tasks that involve abstract reasoning or multimodal content (e.g., combining text and images). This would help to better understand the holistic nature of language processing in the brain and its representation in neural models. Additionally, investigating how these models perform on underrepresented languages or domains with specialized vocabulary could enhance the ability of AI systems to better replicate human language processing. Finally, expanding the scope of neuroimaging techniques used in such studies, such as integrating electroencephalography (EEG) with fMRI, could provide deeper insights into the timing and neural synchrony of language processing.

AUTHOR CONTRIBUTIONS

Look this example below:

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

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

Author 3: Data curation; Investigation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest

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