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Human Cognition versus Artificial Intelligence: A Comparative Psycholinguistic Investigation of Semantic and Contextual Language Comprehension

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ABSTRACT

The rapid advancement of artificial intelligence (AI), particularly Large Language Models (LLMs), has opened new avenues for exploring the ways in which language is understood, interpreted, and produced. Modern AI systems have demonstrated remarkable capabilities in generating text, interpreting sentences, translating languages, and processing contextual information. However, whether these computational abilities genuinely reflect the cognitive processes involved in human language comprehension remains an important question in psycholinguistics and cognitive science. Human language comprehension is not simply a process of recognizing words or constructing sentences. It involves the coordinated functioning of several cognitive mechanisms, including semantic knowledge, memory, contextual awareness, pragmatic interpretation, prior experience, and the ability to recognize communicative intentions. In comparison, LLMs rely on computational architectures trained on extensive textual datasets to identify linguistic patterns, establish contextual relationships, and generate meaningful responses. Despite their impressive performance, the relationship between computational language processing and human cognitive understanding requires further investigation. This study proposes a comparative psycholinguistic framework for examining human and AI-based language comprehension across five major dimensions: semantic interpretation, contextual sensitivity, ambiguity resolution, figurative language, and inferential reasoning.Particular emphasis is placed on distinguishing linguistic accuracy from deeper contextual understanding, as the ability to generate an appropriate response does not necessarily indicate cognitive comprehension comparable to that of humans. Although LLMs can reproduce complex linguistic patterns and perform effectively across diverse language-related tasks, human comprehension remains closely associated with embodied experiences, social interaction, emotional awareness, and cognitive development. The proposed framework seeks to contribute to interdisciplinary research by establishing measurable criteria for comparing biological and computational language processing. It also highlights the potential implications of psycholinguistic research for developing more context-sensitive AI systems and advancing our understanding of human–machine communication.

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1. Introduction

Recent developments in information technology and artificial intelligence have created new opportunities for closer interaction and integration between human beings and technological systems. As a result, increasing research attention has been directed towards the concept of *Human-Aware Artificial Intelligence*,[3] which focuses on developing AI systems capable of functioning as collaborative members of human teams. Such systems are expected to recognize and adapt to the cognitive strengths, limitations, and working patterns of their human counterparts. Concepts such as intelligent partners, collaborative agents, digital companions, and mutual understanding reflect the growing expectation that humans and AI technologies will participate in shared activities within hybrid working environments. For AI systems to function effectively in these collaborative settings, they must be capable of identifying, interpreting, and responding to various dimensions of human behavior, including attention, motivation, emotional responses, creativity, decision-making, planning, and

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argumentation (Krämer et al., 2012; van den Bosch & Bronkhorst, 2018; van den Bosch et al., 2019). Consequently, the development of human-aware AI requires systems with cognitive and behavioral capabilities that facilitate meaningful interaction, coordination, and cooperation with human participants.

Understanding these differences has become particularly important for professionals who increasingly depend on advanced AI technologies in decision-making and collaborative environments, including military organizations, public administration, and policy development. Individuals working alongside intelligent technological systems need to develop an accurate understanding of the capabilities, limitations, and operational characteristics of artificial intelligence in comparison with human cognition. This requirement becomes even more significant as AI applications acquire greater autonomy and become involved in increasingly complex professional activities.[4]

i. Artificial Intelligence vs. Human Intelligence

Artificial Intelligence (AI) refers to computer systems designed to perform tasks that normally require human intelligence, such as problem-solving, pattern recognition, and decision-making. **Human intelligence,** on the other hand, encompasses the ability to think, reason, learn from experience, and **understand emotions** and social contexts. Understanding the differences in **cognition and capabilities** between AI and humans is essential for using technology effectively. It helps set realistic expectations, informs ethical AI use, and guides decisions about when to rely on machines versus human judgment.[5]

ii. Cognitive Abilities Comparison

When comparing artificial intelligence vs. human intelligence, cognitive abilities show some of the most apparent differences. AI and humans process information, learn, and remember in fundamentally different ways, which shapes how each performs in real-world tasks.

iii. Data Processing

AI excels at fast computation and large-scale pattern recognition. It can analyse millions of data points in seconds, making it ideal for tasks like data analysis and image recognition. Humans process information more slowly, but they excel at contextual understanding and meaning. This allows people to interpret nuance, intent, and ambiguity in ways AI systems still struggle to replicate.

iv. Learning Capabilities

AI learns through training data and algorithms, improving performance by identifying patterns in structured datasets. Its learning is limited to the data it has seen and the rules defined by its model. Humans learn from experience, observation, and intuition. People can apply past knowledge to new situations with minimal data, showing flexibility that AI lacks.

v. Memory and Recall

AI systems have perfect recall of stored data and can retrieve information instantly without degradation. This makes AI highly reliable for repetitive or data-intensive tasks. Human memory is adaptive but imperfect. While people may forget details or develop biases, this flexibility supports creativity, emotional learning, and abstract thinking.

vi. Decision-Making and Problem-Solving

In the comparison of **artificial intelligence vs. human intelligence**, decision-making highlights clear strengths and weaknesses on both sides. AI and humans approach problems differently, which affects how they perform in structured versus uncertain situations.

vii. Analytical Decisions

AI makes decisions using data-driven logic and predefined algorithms. This enables it to quickly evaluate large datasets and produce consistent outcomes in rule-based environments. Humans combine logic, intuition, and experience. This blend helps people make judgments when data is incomplete or when emotional and ethical factors are at play.

viii. Creativity and Innovation

AI can generate ideas by identifying patterns in existing data. However, it does not possess true creativity or original intent beyond what it has learned. Humans excel at creative thinking and innovation. People can imagine new concepts, challenge assumptions, and solve problems in original ways.

ix. Handling Uncertainty

AI struggles with novel situations outside its training data. When faced with unfamiliar scenarios, its predictions can become unreliable. Humans adapt quickly to unexpected or ambiguous situations. This adaptability allows people to learn on the fly and make sense of uncertainty.

x. Emotional and Social Intelligence

One of the most significant differences between artificial intelligence and human intelligence lies in emotional and social intelligence. These abilities shape how decisions are made in personal, ethical, and social contexts. Humans possess empathy, emotions, ethics, and moral judgment. These traits allow people to understand others' feelings, consider social consequences, and make value-based decisions.AI does not truly understand emotions. While it can simulate emotional responses using patterns in language or behaviour, it lacks genuine feelings, empathy, and moral awareness. Emotional and social intelligence play a critical role in leadership, teamwork, healthcare, and education. In these areas, human emotional understanding is essential for trust, communication, and ethical decision-making.[6]

xi. Speed, Efficiency, and Accuracy

Artificial intelligence excels in areas that require speed, scale, and consistency. It can analyse massive datasets, recognize patterns, and perform repetitive tasks with high accuracy and minimal fatigue. However, AI is limited by its training data and lacks emotional awareness, moral reasoning, and genuine creativity. Human intelligence, in contrast, is defined by empathy, adaptability, and ethical judgment. Humans can think abstractly, understand social context, and respond effectively to uncertainty.

xii. Strengths of AI

- Rapid computation and large-scale data analysis
- Perfect recall and pattern recognition
- High precision in repetitive or rule-based tasks
- Applications in healthcare, finance, transportation, and automation

xiii. Strengths of Human Cognition

- Creativity, intuition, and abstract reasoning
- Emotional intelligence and empathy
- Ethical and moral judgment
- Flexibility in novel or ambiguous situations

Semantic comprehension focuses on word meaning, while contextual comprehension integrates surrounding linguistic and situational cues, and psycholinguistic research shows that both processes interact dynamically during real-time language understanding. Semantic comprehension involves accessing stored lexical meanings. When a person hears or reads a word, the brain activates semantic networks that represent its meaning. Contextual comprehension uses information from syntax, discourse, speaker intent, and world knowledge to interpret ambiguous or incomplete input. Both processes operate rapidly and often simultaneously, shaping how humans interpret language in real time.

1. Human Cognition and Language Comprehension

Human cognition refers to the mental processes through which individuals acquire, organize, interpret, store, and retrieve information. These processes include perception, attention, memory, learning, reasoning, problem-solving, and language comprehension. Within psycholinguistics, language understanding is considered an interactive cognitive activity in which linguistic information is integrated with knowledge about the world and the communicative situation. The relationship between language and cognition has been examined through several theoretical approaches. Chomsky's work on linguistic competence established an important distinction between knowledge of language and its actual use. Subsequent psycholinguistic research expanded the investigation towards the cognitive processes involved in language production and comprehension. Theories of information processing have also contributed to understanding how individuals recognize linguistic patterns, retrieve lexical knowledge, and construct interpretations. Semantic memory plays a significant role in this process.[7] It enables individuals to connect words with concepts, categories, associations, and previously acquired knowledge. Barsalou

(1999) emphasized the importance of situated conceptualization, suggesting that conceptual knowledge is closely connected with the situations in which it is experienced and used. This perspective is relevant to the present investigation because human comprehension is not restricted to the recognition of textual relationships; it is also influenced by experiential and situational information.

i. Semantic Comprehension and Meaning Construction

Semantic comprehension refers to the ability to identify, interpret, and construct meaning from linguistic expressions. It involves understanding individual words, relationships between words, sentence structures, and the broader conceptual content of a message. The interpretation of meaning is influenced by lexical knowledge, grammatical information, conceptual associations, and background knowledge. For example, the word "bank" can refer to a financial institution or the side of a river. The correct interpretation depends on the linguistic and situational context. Human readers generally resolve such ambiguity by integrating several sources of information. The construction of meaning is also influenced by compositionality, which concerns how the meanings of individual linguistic elements combine to produce the meaning of larger expressions. However, compositional interpretation is not always sufficient because idioms, metaphors, and culturally established expressions may convey meanings that cannot be derived directly from individual words.[8]

ii. Contextual Comprehension and Pragmatic Interpretation

Contextual comprehension refers to the ability to interpret linguistic expressions by considering the circumstances in which they occur. Context may include the preceding discourse, the speaker's identity, the listener's expectations, cultural knowledge, social relationships, and environmental conditions. Pragmatics investigates how meaning is communicated and interpreted beyond the literal content of an utterance. Grice's (1975) cooperative principle and conversational implicative provide a theoretical foundation for examining how listeners infer meanings that are not directly expressed. For example, when someone asks, "Can you open the window?" the intended meaning is generally a request rather than a question about physical ability. Sperber and Wilson's relevance-theoretic approach further explains how individuals interpret utterances by considering contextual assumptions and communicative relevance. Such theoretical perspectives demonstrate that understanding language requires the integration of linguistic expressions with broader interpretive processes.[9] For AI systems, pragmatic interpretation presents both opportunities and challenges. LLMs can identify implied meanings, indirect requests, and conversational intentions in many circumstances. Hu et al. (2023), for example, demonstrated that language models can perform effectively across several pragmatic phenomena. Nevertheless, their findings also indicated that certain social expectations and non-literal interpretations remain difficult.

iii. Artificial Intelligence and Computational Language Processing

Artificial intelligence is a broad technological field concerned with developing computational systems capable of performing tasks associated with intelligent behavior.AI applications frequently rely on NLP, machine learning, deep learning, and neural network architectures. Earlier NLP systems generally depended on linguistic rules, manually designed representations, and statistical methods. Although these approaches achieved useful results, they faced limitations in processing complex language patterns and context-dependent expressions. The introduction of transformer architectures represented a major development. Vaswani et al. (2017) proposed an attention-based architecture that enabled models to capture relationships between different positions within a sequence. Subsequently, BERT, introduced by Devlin et al. (2019), demonstrated the effectiveness of bidirectional contextual representations for various language understanding tasks. The emergence of generative language models further expanded the capabilities of computational language processing. Brown et al. (2020) demonstrated that large-scale language models could perform a range of tasks through appropriately designed textual prompts.

2. Large Language Models and the question of understanding

LLMs are neural network-based systems trained to model patterns and relationships within large collections of linguistic data. Their ability to generate fluent language has encouraged researchers to investigate whether their outputs reflect meaningful semantic and contextual competence. Bender et al. (2021) raised important concerns regarding the interpretation of language-model performance, particularly the distinction between linguistic form and meaning grounded in social and experiential contexts.[10] Their discussion highlights the need to examine the limitations of evaluating language models solely through their generated outputs. Mahowald et al. (2024) further distinguished formal linguistic competence from functional linguistic competence. This distinction is relevant because a system may produce grammatically appropriate language without demonstrating equivalent abilities in social reasoning, goal-directed communication, and real-world understanding. Connell and Lynott (2024) argued that language models can contribute to research on human cognition, but their usefulness as cognitive models depends on whether their learning mechanisms and representations are psychologically plausible.

Consequently, the present study adopts a comparative perspective that recognizes the linguistic capabilities of LLMs without assuming that their computational processes are equivalent to human cognitive mechanisms.

4. Research Objectives

1. To compare semantic comprehension abilities between human participants and AI models.
2. To investigate differences in contextual language interpretation.
3. To examine the ability to interpret ambiguity, figurative expressions, and implied meanings.
4. To evaluate the role of contextual information in human and AI language comprehension.
5. To identify the cognitive and computational strengths and limitations of both systems.

5. Research Questions

1. How do human participants and AI models differ in semantic language comprehension?
2. To what extent do humans and AI interpret context-dependent expressions accurately?
3. How effectively do humans and AI resolve linguistic ambiguity and figurative meaning?
4. What differences emerge in inferential reasoning and pragmatic interpretation?
5. What are the distinctive strengths and limitations of human cognition and artificial intelligence in language comprehension?

Task	Area of investigation
Semantic interpretation	Word and sentence meaning
Contextual comprehension	Context-dependent meaning
Ambiguity resolution	Lexical and syntactic ambiguity
Metaphor interpretation	Figurative language
Pragmatic comprehension	Implied meaning and intentions
Inferential reasoning	Drawing conclusions from text

6. Research Instruments

A structured psycholinguistic assessment instrument will be developed to examine six dimensions of language comprehension.

Linguistic Dimension	Experimental Task	Measurement
Semantic comprehension	Word and sentence interpretation	Correct interpretation
Contextual comprehension	Context-dependent sentences	Contextual accuracy
Ambiguity resolution	Lexical and syntactic ambiguity	Correct disambiguation
Figurative language	Metaphors and idioms	Interpretation accuracy
Pragmatic comprehension	Indirect requests and implied meanings	Intended meaning
Inferential reasoning	Short passages and conclusions	Valid inference

Approximately 36 experimental items may be developed, with six items assigned to each dimension. A larger item bank may be prepared to allow counterbalancing and reduce the influence of repeated exposure. The instrument should undergo expert review and pilot testing before the main study. Psycholinguists, English-language specialists, and computational linguistics researchers may evaluate the clarity, relevance, and linguistic validity of the items.[11]

i. Experimental Procedure

The experiment will be conducted in two parallel conditions.

- **Human Condition :** Participants will receive the comprehension tasks through a standardized questionnaire or computer-based interface. They will be instructed to read each linguistic expression and select or provide the most appropriate interpretation. Response accuracy and response time will be recorded.
- **AI Condition :** The same linguistic stimuli will be presented to the selected LLMs through a standardized prompting protocol. The instructions will specify the expected response format and prohibit access to external information during the evaluation

where technically feasible. Each model will be tested under documented conditions. Multiple trials may be conducted to assess response consistency. The study should preserve the exact prompts and outputs to support reproducibility.

ii. Data Collection and Ethical Considerations

Human participants will be informed about the purpose of the research, the voluntary nature of participation, and the confidentiality of their responses. Informed consent will be obtained before data collection. Personal identifying information will not be included in the analytical dataset. Participants will be free to withdraw according to the approved research protocol. The AI evaluation will document model versions, prompt templates, testing dates, temperature settings where available, and other relevant parameters. Since commercial models may be updated, these details are essential for reproducibility. The study should obtain institutional ethical approval where required.[12]

7. Descriptive Statistical Analysis

Descriptive statistics will be used to summaries participant characteristics and performance across the six linguistic dimensions. The principal measures will include:

- Mean accuracy.
- Standard deviation.
- Median response time.
- Correct and incorrect response frequencies.
- Response consistency across repeated trials.

Accuracy will be calculated as:

{

$$\text{Accuracy}(\%) = \frac{\text{Number of Correct Responses}}{\text{Total Number of Valid Responses}} * 100$$

}

Where :

- **Number of Correct Responses :** Total number of correctly predicted or classified instances.
- **Total Number of Valid Responses :** Total number of evaluated instances.

The calculation will be applied separately to each linguistic dimension and experimental condition.

i. Comparative Statistical Analysis

The comparison will examine whether differences in performance are statistically meaningful.

Depending on the experimental structure and distribution of the data, the following methods may be employed:

1. Independent-samples or mixed-effects models for group comparisons.
2. Logistic regression for binary response accuracy.
3. Repeated-measures analysis for contextual conditions.
4. Response-time analysis for human participants.
5. Effect sizes and confidence intervals to estimate the magnitude and precision of observed differences.

Because AI outputs are not independent human observations, statistical models must account for clustering by participant, item, model, and repeated trial where appropriate. Model-generated responses should not be treated as if they were additional human participants.[13]

ii. Qualitative Response Analysis

Qualitative analysis will examine the nature of successful and unsuccessful interpretations.

Responses may be classified into the following categories:

- Literal interpretation.
- Contextually appropriate interpretation.
- Incorrect semantic interpretation.
- Incomplete interpretation.
- Pragmatic misunderstanding.
- Unsupported inference.

- Ambiguous or inconsistent response.

Independent human evaluators should assess open-ended responses using a predefined coding framework. Inter-rater reliability may be estimated using Cohen's kappa or another appropriate agreement statistic.[14]

iii. Proposed Evaluation Framework

The study proposes six principal evaluation dimensions:

Dimension	Description
Semantic accuracy	Ability to identify intended linguistic meaning
Contextual sensitivity	Ability to integrate surrounding information
Ambiguity resolution	Ability to distinguish alternative interpretations
Figurative interpretation	Ability to understand non-literal expressions
Pragmatic competence	Ability to infer communicative intentions

These dimensions provide an integrated basis for examining human and AI language comprehension.

8. Semantic Comprehension

The first analytical dimension will examine the ability of human participants and AI models to interpret words, phrases, and sentences. Particular attention will be given to expressions with multiple meanings and sentences whose interpretation depends on the relationships between individual linguistic components. The analysis will investigate whether the systems identify the intended meaning consistently across familiar and unfamiliar expressions. It will also examine whether incorrect responses arise from lexical confusion, grammatical interpretation, or insufficient contextual integration.

i. Contextual Language Comprehension

The second dimension will examine the influence of contextual information on interpretation accuracy. Participants and AI systems will receive sentences presented under different contextual conditions. These conditions may include high-context, low-context, and misleading-context situations. The analysis will establish whether additional information improves interpretation accuracy and whether the improvement is comparable across the two groups.

ii. Ambiguity Resolution

This dimension will investigate the interpretation of lexical and syntactic ambiguity. For example, the sentence "I saw the man with the telescope" may have more than one interpretation depending on whether the telescope is understood as the instrument used for seeing or as an object possessed by the man.[15] The analysis will examine the extent to which participants and models identify alternative interpretations and use surrounding information to select an appropriate meaning.

iii. Figurative and Metaphorical Interpretation

The fourth dimension will examine metaphors, idioms, and non-literal expressions.

Examples may include:

- "Time is money."
- "She has a heart of stone."
- "The classroom was a zoo."
- "He broke the ice."

The analysis will determine whether participants and AI systems identify figurative meanings rather than relying exclusively on literal interpretations.

iv. Pragmatic Interpretation

Pragmatic comprehension will be evaluated through indirect requests, conversational implicatures, politeness, and implied intentions or example, the statement "Would you mind closing the door?" is grammatically structured as a question but ordinarily functions

as a request. The analysis will consider whether the systems recognize the intended communicative function and whether their interpretations remain consistent when the social context changes.[16]

v. Inferential Reasoning

The final dimension will examine the ability to draw conclusions from short passages and contextual descriptions. The assessment will distinguish between conclusions supported by the supplied text and interpretations that depend on assumptions not justified by the available information. This distinction is important because a linguistically fluent response may nevertheless contain an unsupported inference.

Table-1 : Qualitative Comparison of Interpretation Patterns

Evaluation area-	Human Cognition	AI-based Language Processing
Background knowledge	Draws upon personal and socially acquired knowledge	Uses learned information and available context
Contextual interpretation	Integrates linguistic and situational experience	Uses contextual patterns and prompt information
Ambiguity	Uses context, expectations, and experience	Uses learned associations and supplied context
Figurative language	Draws upon conceptual and cultural knowledge	Generates interpretations from learned linguistic patterns
Pragmatic meaning	Uses social interaction and communicative expectations	Infers likely intentions from linguistic and contextual cues
Inference	Combines textual evidence with world knowledge	Generates conclusions through computational processing

9. Discussion

The comparative framework highlights the fundamental differences between human language comprehension and AI-based language processing. Although humans and Large Language Models (LLMs) may produce similar linguistic responses, their underlying processes are not necessarily the same. Human comprehension is shaped by experience, perception, emotions, cultural background, social relationships, and contextual knowledge, whereas LLMs primarily rely on computational patterns learned during training and information provided through prompts. Previous studies by Hu et al. (2023) and Dentella et al. (2024) [17] demonstrate that AI models can exhibit certain pragmatic abilities while still showing limitations in understanding complex linguistic and contextual information. Similarly, Mahowald et al. (2024) distinguish between linguistic competence and the practical ability to use language effectively in real-world situations. Therefore, a meaningful comparison between human cognition and AI should consider not only linguistic accuracy but also contextual interpretation, pragmatic understanding, and the ability to respond appropriately to different communicative situations.

10. Implications

i. Implications for Psycholinguistics

The proposed study contributes to psycholinguistic research by bringing biological and computational language processing into a common comparative framework. It encourages researchers to investigate the relationship between semantic knowledge, contextual interpretation, pragmatic inference, and language prediction. It may also help identify which aspects of linguistic competence can be reproduced through computational learning and which require further theoretical explanation. [18]

ii. Implications for Cognitive Psychology

The research offers opportunities to examine how memory, attention, prior knowledge, and inferential reasoning contribute to human language comprehension. Comparative analysis may help researchers distinguish between observable linguistic performance and the underlying processes responsible for that performance.

iii. Implications for Artificial Intelligence

The findings may provide useful guidance for developing more reliable and context-sensitive language models. AI developers may benefit from evaluation procedures that examine contextual consistency, ambiguity resolution, pragmatic interpretation, and evidence-based inference rather than depending exclusively on general language benchmarks.

iv. Implications for Education and Language Learning

The investigation may also contribute to English-language teaching and learning.AI-based language assistants can support learners through explanations, contextual examples, vocabulary development, and feedback. Nevertheless, teachers remain important in helping learners understand cultural meanings, social communication, emotional expression, and the relationship between language and real-life experience. A human-centred approach to AI-assisted language education may therefore provide a productive balance between computational efficiency and pedagogical understanding.

v. Implications for Human–AI Collaboration

Rather than treating AI and human cognition as competing forms of intelligence, the proposed research encourages an approach based on complementary capabilities. AI systems may provide rapid information processing and large-scale linguistic analysis, while human users contribute contextual judgment, experiential knowledge, ethical reasoning, and social understanding. Such collaboration may improve the quality of communication, education, research, and other language-dependent activities.[19]

11. Conclusion

The comparison between AI and human intelligence reveals a complementary relationship rather than a competition. AI shines in areas requiring rapid data processing, problem-solving, and decision-making, especially in structured environments where speed and precision are key. Meanwhile, human intelligence excels in creativity, emotional understanding, adaptability, and the ability to learn from limited data and experiences. The development of artificial intelligence, particularly Large Language Models, has transformed the study of language processing and generated important questions about the nature of human language comprehension. Contemporary LLMs can perform sophisticated linguistic tasks, including semantic interpretation, contextual response generation, summarization, translation, and pragmatic inference. Their capabilities demonstrate the considerable progress achieved in computational linguistics and NLP. However, human language comprehension remains a complex cognitive activity involving the interaction of linguistic knowledge, memory, perception, experience, contextual awareness, and social communication. Human beings interpret language not merely as an arrangement of words but as a meaningful activity embedded in personal and social environments.[20] The present paper proposes a comparative psycholinguistic framework for examining human cognition and AI-based language processing across six dimensions: semantic comprehension, contextual sensitivity, ambiguity resolution, figurative interpretation, pragmatic competence, and inferential reasoning The paper concludes that human cognition and artificial intelligence should be understood as distinct yet potentially complementary systems of language processing.

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