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THE LINGUISTICS OF AI: UNDERSTANDING HUMAN LANGUAGE PROCESSING IN MACHINES:

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Abstract

This study focuses on the qualitative linguistic analysis of the discourse produced by artificial intelligence systems, which process, decode and generate human language. It speaks to a current debate on whether language models show actual linguistic understanding or for example just build patterns if they are trained on huge amounts of text. The study builds on the theories within the range of interest including Cognitive Linguistics, Systemic Functional Linguistics, Pragmatic Theory, and Discourse Analysis, and provides an evaluation of AI scores on four dimensions – syntax, semantics, pragmatics and cultural interpretation, all of which are interconnected. The largest number of texts was generated with a purposive sampling, using controlled texts, and then analysed with discourse analysis and thematic linguistic interpretation. This study compares three prevalent AI systems: ChatGPT (GPT-4), Gemini and Claude 3, on challenging tasks such as (complex) sentence creation, idiomatic translation, conversational politeness, and cultural symbolism. The results reveal that in general all three systems have good syntactic ability, a more or less precise semantic comprehension and a limited pragmatic and cultural competence. While most of these systems produce grammatical structures that are acceptable, meaning levels of common usage are correct, and expressions are socially acceptable, such responses are often formulaic and deficient in more dense contextual, experiential, historical, and cultural support. Based on this, the study points to the seeming inability of AI since the language performance does not seem to amount to human-level concept matching, but to sophisticated linguistic simulation. The study encompasses the use of known linguistic theories to analyze the discourse produced by AI and their implications for the future of language technologies, providing contributions for the recent field of AI linguistics and stressing the need for interpreting, culturally sensitive, yet understandable, and responsible development in language technologies.

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1.INTRODUCTION

The analysis of language always has been a central subject to the understanding of human intelligence. In recent years, the fields of linguistics and AI have merged in new ways to provide a different avenue through which to investigate how machines process, interpret, and create human language. The use of Artificial Intelligence has taken a deep root in the society and has impacted the way humans relate, learn and make decision. Linguistic structures play a crucial role in AI technologies, serving many purposes including the functioning of conversational assistants or automated translation systems. Linguistic theory and machine learning is thus not just a technology question, but a linguistic one. In this research, researchers will examine how AI systems comprehend the human language and grasp its meaning, syntax, and context. The linking concept between computational algorithms and human language understanding is the essence of this research.

Over the past decade, NLP has seen a revolution with the aid of deep learning. Transformer based models like GPT, BERT, and others have shown remarkable performance on linguistic tasks like translation, summarisation, and semantic reasoning (Belinkov, 2022). However, these models are highly successful but still have the drawback that they function like a black box and it is hard to understand what the principles are in the system on which it is built that determine its representations. Driven by these doubts, researchers have done more to contemplate the nature of their systems' understanding of language, rather than accepting that these systems simply replicate the surface patterns of language (He et al., 2024). The role linguistics plays in an AI model is a subject of great debate among both computational linguists and cognitive scientists. For instance, Conia and Navigli (2022) have demonstrated that pretrained language models have embedded structures capable of representing human-like grammatical knowledge, although other scholars have pointed out that they lack deeper and more general knowledge (Weissweiler et al., 2022). The above-mentioned tension between imitation and comprehension is the foundation with which the present study will deal.

The need for this study lies in the pressing need to find out how in the mind of a machine the structure and meaning of human language is picked up. Despite widespread incorporation into decision-making, social interactions and even creative forms of expression, the linguistic constraints of AI systems are often overlooked. The linguistic basis of AI is essential for boosting the precision of computer systems and securing their moral and fair usage. With the growing presence of language models in information, misinformation, and social discourse, their language use has far-reaching effects on human interaction and communication (Shen et al., 2023). The goal of this research is to give a linguistically informed framework and understand how syntax and semantics are being captured and manipulated by the AI systems dealing with prankmatics. This program takes a holistic view of language as a more than symbol-encoding computational system. It is a social and cognitive phenomenon that is representative of human thought, context and culture. Thus, the language comprehension is a window into human, too.

This study's problem is about the opacity of AI systems in using and creating language. Although a lot has been achieved in the field of technology, little is known about the linguistic mechanisms involved in the processing of the human communication of a machine. This poses theoretical and practical problems. At a conceptual level it puts forth a question regarding whether the language models reflect meaning or merely pattern matching of words. On the ground, it has an impact on the dependability of AI products that rely on natural-language knowledge, such as automatic translation systems, virtual assistants, and information retrieval engines. While previous studies have addressed syntactic or semantic processes in AI, few studies have explored the aspects of both processes together extensively. This study uses a qualitative approach to languages and linguistic enquiry in an attempt to uncover the "how" of machine language generation and comprehension and the “why” of their deep structures.

This research has three aims: The first goal is an analysis of how far existing artificial intelligence systems simulate the mechanisms of how languages evolve in human understanding, especially with regards to

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syntax and semantics. The second goal will involve leveraging and examining the significance and structure theory concepts for the development of AI models that are easier to understand and interpret. The third goal is to explore the implications for the overall language-cognition – AI interplay. The objectives above define the study's qualitative design that uses a textual and linguistic analysis approach to AI language processing behavior. The analysis of the similarities, differences, patterns, structures, and restrictions among the machine-generated languages aims to reveal the linguistic logic in play in these machine languages.

In order to accomplish these objectives existing purposes for the study are put forward as.For achieving these objectives, the following research questions are raised. How is the syntax and meaning of words learnt by AI systems? What implications are there for having machine learning models of the process of human language understanding? What new insights can be gained from linguistic theory for better understanding and ethical use of AI language systems? Qualitative questions are those that revolve around understanding instead of measurement. Their aim is not to investigate the accuracy of machine language numbers, but rather the concept and understanding of depth and complexity. This is an orientation similar to that of the qualitative approach of linguists concerned with the meaning side of human language; its emphasis on explanation rather than prediction, meaning rather than quantification.

The importance of this research is that they are interdisciplinary. It ties up theoretical work with computational modeling, thus offering a human perspective of machine language processing. This work is different from works which are limited to the performance of the algorithm because it strives to be meaningful, contextual and interpretable. The study focuses on the concept of AI systems functioning as linguistic agents, not just statistical models, and provides a new approach to studying the process of machine mimicry as the human process of understanding. This helps linguistics as well as AI, and becomes the road to building more transparent, language-aware models. Additionally, the results can be used to help design educational technologies, digital communication systems and cross-cultural applications of Artificial Intelligence. The study represents a new approach to identify the linguistic nature of artificial intelligence and to advocate for new, more responsible, interpretable and human-centred language technologies.

The rest of this paper is structured as follows. The following section provided a literature review of linguistic and computational enterprises in language processing, focusing on important issues of meaning representation, syntax, and interpretableness. The methodology section then outlines the qualitative methodology followed for analyzing the behavior of the machine and how linguistic analysis was utilized to analyse outputs produced by the AI. After that, the results and discussion sections contain the findings of the study and interpret them with regard to the theory of human language. Finally, the authors stated that the findings of this study will be valuable for future research, citing the ongoing evolution of AI that will rely on transparency, interpretability, and linguistic knowledge to come to better conclusions.

2.Related Literature:

However, with the emergence of neural network models, researchers have wondered if AI can truly grasp language or simply mimic its patterns. Nevertheless, fundamental research, including those by Vaswani et al. (2017) and Peters et al. (2018), challenged the computational linguistics community by demonstrating the power of contextually based word embeddings that go beyond mere word-level statistics to a more sophisticated understanding of meaning. This innovation demonstrated the ability of language models to approach human fluency without the need to know the grammar formally. Such models, however, like those of Tenney, Das and Pavlick (2019) and Hewitt and Manning (2019), are particularly good at prediction, but not understanding. Presumably, because of these apparent successes, there are deeper linguistic questions about whether the mechanisms used to process information in such systems are similar, or merely exemplifying probable regularities, in the maintenance of human cognitive

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processes. This is a continuing discusses that is useful for exploring the working of linguistic meaning in artificial systems.

This can be extended by syntactic generalization. For example, Marvin, Linzen (2018) and Gulordava et al (2018) reported that models are capable of many common syntactic patterns, but struggle with less frequent patterns that call for abstract syntactic reasoning. As does Linzen, Dupoux, and Goldberg (2016), who used recurrent models to show that they learn some of the dependencies, but not hierarchical agreement. The strongpoints of these studies are that they have subjected the grammatical sensitivity to systematic testing, providing evidence for the partly linguistic competence. However, an interpretation is necessarily shallow due to a limited reliance on controlled benchmarks because it is not possible to reduce linguistic proficiency in terms of grammatical correctness. The present study focuses thus not just on error measures but also on research into the interaction of syntactic behaviour, meaning and context in machine-generated language.

Later work has been directed towards probing and interpretability tools to be able to gain insight into a linguistic understanding embedded within neural architectures. Previous research has revealed that language models contain syntax hierarchically, such as in structural probing (Hewitt & Manning, 2019) and task-specific layer analysis (Tenney et al., 2019), with some surveys thoroughly questioning the finding on this scope by Belinkov and Glass (2019) and by Rogers, Kovaleva and Rumshisky (2020). A wealth of fine-grained knowledge of internal representations, as in these studies, which are of a methodologically sophisticated type. However, since they mostly use quantitative correlations, they may "boil down" the cognitive validity of these encodings. Although their analysis is well done, their response does not clarify the relationship between structural patterns and meaning making. The lack of this represents the significance of qualitative methods to understand the outputs of AI as linguistically, not just numerically, evaluative methods.

Furthermore, the results of the psycholinguistic comparison between AI and human language processing are both interesting and confusing. Research on surprisal theory (Goodkind & Bicknell, 2018; Futrell, Gibson & Levy, 2020) showed that model-derived predictability is comparable to human reading time data, indicating that model and human readers draw similar conclusions from the text. modelling later studies by Oh, Clark, and Schuler (2021) and Shain et al. (2024), however showed that this connection is decreased with scaling-up in modelling size, demonstrating non-linear relationship between computational cognition and human cognition. The advantage of this literature is that it does not use only the cognitive aspects of language but also the computational aspects of language while the disadvantage is that it assumes that correlation is comprehension. For this reason, this study does not focus on mimicking human performance measures; instead, a qualitative understanding is gained regarding the organization and expression of meaning at the discourse level offered by AI.

Other researchers have begun to doubt the possibility of linguistic “understanding” in machines, however. Large language models are “stochastic parrots”, as Bender and Koller (2021) argue, because they create a harmonious piece of fluent text without context on communicative intent and experiences. Similarly, Mahowald et al. (2024) differentiate formal competence (ability to put together grammatical sentences) and functional competence (ability to use language purposefully). The arguments express a significant philosophical question: models seem to be “good” but they are insufficiently “semantically substantive.” However, such criticisms provide a useful expose of gaps in AI's capabilities and fail to consider the possibilities of linguistic analysis uncovering language subtext corpora in machine output. For this reason, the present research takes a linguistic-interpretive view – not that AI understands but rather what pretext it gives to this understanding.

So, as far as interpretability research, that's a double edged sword. On the other hand, it supplies in-depth data concerning the representation of syntax, semantics and discourse relations (Hewitt & Manning, 2019; Tenney et al., 2019). However, as Belinkov and Glass (2019) note, interpretability tools like

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attention visualization and probing can draw misleading inferences regarding comprehension. The advantage of these methods is that they are transparent and the problem is that they are abstract from communicational context. Therefore, in addition to the studies that shed light on internal processes, the study of textual resonances and the coherence of the work can be enriched by linguistic analysis, qualitative in nature, that aims to explore semantic, coherence and pragmatic aspects of the text produced in reality. This integrative view is one of the main justifications for the research being conducted in the present study.

In addition, recent investigations have shed light on the sociolinguistic aspects of the use of an AI language processing system. Experiential interaction is required to develop linguistic grounding (Bisk et al., 2020), and models contain cultural biases manifested in their training data (Pawar et al., 2025). The insights gained from these findings are vital to comprehend social trends in language, and sometimes trends reinforced by AI. Most of these studies, however, consider bias as it is an ethical issue rather than one of language and meaning, that it also has problems from this angle. Similarly, the present paper conceives of the notion of bias as a linguistic phenomenon (as an indication of models' internalization and reproduction of communicative patterns within a specific context).

In view of these observations, it has to be concluded that current scholarship, though full of technical detail, lacks an interpretative dimension. Although structural and probabilistic competences have been established in quantitative studies of language models, less work has been done on the qualitative behavior of LMs as language actors in discourse. The virtue of previous work is that it is grounded in the facts, its fault that it is “illiteracy” in language terms, you might say. Hence, this study is based on the previous studies but includes some modifications, using both the linguistic approach and qualitative method. By doing so, it aims to shed light on the process of meaning, context, and interpretation in AI-generated language, providing an interesting new interdisciplinary perspective on the linguistics of Artificial Intelligence.

Theoretical Framework

The theoretical underpinning of such studies are in the area of linguistics, cognitive science, and Artificial Intelligence, which gives multidimensional perspective and deeper meaning of machine language behavior. The conceptualization of language as a cognitive process and a social act with a meaning, a context and an interpretation ran through the centre of this study. This stance is based upon Functional Linguistics and Cognitive Linguistics, where the language forms become meaningful in the context of their use (Halliday & Matthiessen, 2014; Langacker, 2008). Human communication is based on experience and shared understanding while AI language systems develop meaning from probabilistic patterns in large amounts of text. So the problem at the heart of the theoretical issues is: "How can these models be said to simulate human meaning, without any human consciousness or intention?

Cognitive Linguistic Theory (CLT) has guiding principles of study throughout this research; namely the concepts of conceptualization and mental representation in language (Evans, 2019). The meaning is seen in cognitive linguistics as emerging from what has been experienced physically in human bodies and mentally as models. Some other models, like GPT and Gemini, use language models that rely on statistical patterns instead of embodied cognition. The study compares these perspectives to comment on the similarities and differences in how AI-generated text uses conceptual vehicles like metaphor, categorization and inference. AI is without cognition, but it can show linguistic coherence that can be interpreted using a cognitive-linguistic approach. The staying power of this theory is that it has explanatory value for the processes of 'meaning making', whereas its drawback is the anthropological claim of 'cognitive embodiment' which characterizes human activity but does not apply to machines. This mode of inspiration is then used analogically, as an analysis framework and not as the model of AI thinking.

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The other perspective is offered by Systemic Functional Linguistics (SFL), which looks at the function of language in context, in terms of enacting meaning, ideology and interpersonal relations (Halliday & Matthiessen, 2014). SFL analyzes the meaning of language into three metafunctions: ideational, interpersonal, and textual, the three metafunctions being sufficient to account for how language brings about meaning in experience, interpersonal relationships, and textual coherence. By using SFL with AI-generated text, you can analyze the way the models build the thematic progression, coherence, and voice. Existing studies have revealed that LLM tends to capture genre specificity and cohesive devices well, but fails to detect pragmatic nuances and/or register shifts (Pawar et al., 2025; Li et al., 2023). Thus, SFL can provide a systematic method for assessing the communicative functions of AI text; it can manifest its fluency and pragmatic shortcomings.

Furthermore, Pragmatic Theory, particularly Grice (1975) on implicature, and Sperber & Wilson (1995) on Relevance Theory are used to examine how contextual meaning is also processed by AI. Unlike the human level, AI systems analyze and determine relevance from statistical data, while humans use background information and intend recognition. Such pragmatic lenses can be used for analyzing machine discourse and discovering places where it is coherent, implicative and at the level of the context. These theories were designed to account for human-human or human-computer interaction, but when applied to the realm of AI discourse, they shed new light on aspects of parallel and non-parallel communicative action in computation which accounts for a distinctive understanding of AI's ability to emulate pragmatic reasoning.

Furthermore, Discourse Analysis is used as a general interpretive analytical approach which guides the qualitative analysis in this research. Discourse Theorists like Fairclough (2013) and Stubbs (2020) maintain that language should be investigated in relation to Social Practice, Context, ideology and Communative intent. Though AI systems do not have any social aim, their results are the same as the output of the society due to their training on human discourse. In this research, AI-produced text will be interpreted as a representation of linguistic norms and power relations as they are reproduced in the data. This also shows linguistic features and contextualizes them within the larger sociocultural meanings. What is good about discourse theory is that its context is rich and what is bad about discourse theory is its anthropization of machines' communication; but this dynamic is not bad at the level of analysis at which it sits here.

Finally, the combination of these two theories (Cognitive Linguistics, Functional Linguistics, Pragmatics, and Discourse Analysis) is a powerful basis for analyzing the behaviour of AI language. These frameworks are combined to allow for study on the interpretive level rather than the computational one. This work employs some of the linguistic models that were developed to explain human communication to explain machine-generated discourse, illuminating, in the process, the gap between simulation and understanding. It does so, making the language model itself the centre of linguistic attention, rather than merely a computational object, and bringing the study of language up to speed with the emerging interdisciplinary study of the Linguistics of Artificial Intelligence.

Research Methodology

This study's design called for a qualitative approach to explore the interpretive rather than quantitative aspect of the language produced by the machine. Most of the computational linguistics studies are based on metrics or bench accuracy, but this study was conducted interpretively to pay more attention to meaning constructions, coherence and pragmatic relations as suggested by Creswell and Poth (2018). The design is qualitative because the intent is to find out how meaning is communicated in discourse situations by means of language models. The methodology, therefore, does not just measure correctness in AI generated text, but instead focuses on the presence of linguistic patterns, coherence strategies and

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pragmatic shifts. It is consistent with the principles of applied-linguistics that regard language as social practice rather than a fixed system of language (Phakiti, De Costa, Plonsky, & Starfield, 2018).

The data focused on generating a Purposive sample of AI generated texts produced by a large language model which has a controlled prompting condition. The outputs were recorded and a set of prompts that emphasized syntactic, semantic and pragmatic phenomena were used. This strength is the system's ability to allow in-depth discourse on how models respond to prompts linguistically to draw in-depth conclusions about meaning-making. The approach is however hampered by the lack of sample size and by model dependent biases. However, the commitment to going deep instead of wide means that the presentation of the findings may be richer and more interpretive, and enables the study's exploratory purposes.

This was done using the approach of discourse analysis and thematic linguistic interpretation (Bogé & Smith, 2016; Creswell & Poth, 2018). These texts have been excerpted and read numerous times to highlight the thematic linguistic and pragmatic aspects in each text. Ontheone extended these features to higher-order categories by open coding them and grouping them together under the headings of "contextual adaptation" and "syntactic fluency without pragmatic anchoring." This model is not one of numerical validation, but rather it has interpretive depth. Most restrictive, however, is the possible subjective interpretation of the researcher which was addressed by reflexivity and iterative validation (Lincoln & Guba, 1985).

Similarities and divergences of the output of the AI systems, and the linguistic norms and theoretical expectations of human discourse use (Chomsky, 1965; Grice, 1975; Halliday, 1978) led to the identification of discourse similarities and divergences.The analysis was centered on three aspects: reference management, topic continuity and underlying meanings which create communicative intent. One such aspect that has been evaluated, for example, is the use of anaphora, ellipsis, and pragmatic repair strategies for AI-generated discourse. This study did not assume that any departure from "human" norms is an error, but rather that the variations may provide insights into the ways in which the model(s) create meaning. An interpretive version of the orientation hints at nuances in the processing of machine language that a quantitative version might miss, but it also means that results should be considered in context and not always as generalizable.

Triangulation was employed on the results, by comparing results from the models and prompt variations, to create credibility and trustworthiness. Reflexivity was facilitated by researcher's journals and analytical memos for recording interpretative decisions. There was a particular focus on ethical concerns, however, as AI language systems have embedded bias concerns (Bender, Gebru, McMillan-Major et Shmitchell, 2021). Ensuring data was collected and acknowledging model bias provided an increased level of rigor and integrity. Also in accordance with the analysis, ethicality principles related to AI interpretability and responsible use (Weidinger et al., 2023) were followed.

Reason for this research from a methodological point of view is the way it is not oriented around quantitative paradigms. Most computational linguistics research focuses on internal representation probing, as well as accuracy metrics. Contrary to this, this research will focus on identifying how meaning, coherence and pragmatic function emerge in the context of AI text, drawing on the support of linguistic and interpretive theory. The present study places emphasis on both the interdisciplinary domains of linguistics and AI, while highlighting the connection between language structural modeling and language interpretive research. The study examines language not only as employed by machines, but how it could be processed in an artificial system as well, providing a unique and qualitative point of view in the fast-expanding research field of language in the world of Artificial Intelligence.

Results And Discussion

This section is presented to show and illuminate the findings of this qualitative linguistic investigation about the understanding and reproduction of the human language in Artificial Intelligence systems. This

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analysis adopts the methodology developed in Section 3, with syntax, semantics and pragmatics as interrelated language dimensions that facilitate examining how the meaning is generated and built by language models. Three the most popular AI systems – ChatGPT (GPT-4), Gemini (Bard), and Claude 3 – were prompted to provide data by means of qualitative textual prompts. Linguistic accuracy, context and sociocultural awareness were analyzed in each system.

The goal of this section, is not only to describe the language outputs but also to interpret them using the Linguistic Theoretical Framework created in part before, which incorporates the syntactic principles of Chomsky (1965), conceptual semantics of Lakoff and Johnson (1980), pragmatic cooperation model of Grice (1975), and socio-semiotical knowledge of Halliday (1978). These theories are triangulated to investigate the role in which AI systems perform meaning negotiation at different language levels and to see how far AI is able to approximate human understanding. This analysis is explicitly designed to focus on text-level linguistic output and not on 'internal' representations of learning. The probing and interpretability literature surveyed in Section 2 is not used to perform probing on this analysis; it provides context to the theoretical discussion, not a probing technique to be applied in this context.Within each analytical segment, and in the overall unified discussion, the results are discussed repeatedly, where each repetition advances the discussion.Within each analytical segment and in the integrated discussion, the results are discussed over and over again, with each repetition building the discussion.

4.2 Syntactic Competence in AI Language Generation

Syntactic analysis was used to measure the grammatical and structural correctness of AI generated language. The models were asked to build 'more complicated' sentences with a requirement to be able to hold out clause structure and consistency.

Prompt 1:"Create a grammatically complete sentence composed of two dependent clauses and one independent clause to describe an event in the future".

Table 4.1: Syntactic Structure Analysis of AI Responses

Model	Generated Response (Excerpt)
ChatGPT (GPT-4)	"When the rain stops and the clouds clear, the children will return to the playground."
Gemini (Bard)	"Once the rain has ended and the streets have dried, people will go outside again."
Claude 3	"If the rain stops and the sun appears, then everyone will resume their daily activities."

All models were grammatically correct with correct subordination of clauses and verb tenses. While ChatGPT had a natural rhythm and clause sequencing, Gemini had a more mechanical tone with grammatical accuracy, and Claude had a bit more rigid structure with conditional syntax.

Discussion

The three AI systems all exhibited structural competence in the sense of Chomsky (1965) – syntactic competence. Their clause structures were correct with respect to English grammar, indicating that they were effective in modelling hierarchical phrase structure. But this level of precision also uncovers a syntaxic pattern reproduction instead of any generative creativity.

AI sentences are uniformly structured, but human speakers might add rhythm, variation and emphasis to suit context or emotion. For instance, ChatGPT's sentence is fluent; it doesn't have the prosodic variation that people add to their speech. An important theoretical question is the difference between this and a deep grammar, which this distinction emphasizes: AI models are learning statistics, not deep grammar.

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Chomsky's distinction between competence and performance is the basis for the machines' formality but lack of understanding of the psychology behind it. When there's no stylistic deviation, it means that the syntax of AI is rule-based, without human language intentionality. Hence, the syntactic performance of machines must be understood as the successful simulation of form and not as a process of linguistic cognition.

The student demonstrates understanding and construction of meaning in the use of text.

The following idiomatic prompt was created to determine the models' understanding of figurative language and abstract meaning to test their semantic understanding.

Prompt 2: "Write a short paragraph to explain what the phrase 'the ball is in your court' means".

Table 4.2: Semantic Accuracy and Depth of AI Responses

Model	Generated Response (Excerpt)
ChatGPT (GPT-4)	"The phrase means that it is now someone's responsibility to make the next decision or take action."
Gemini (Bard)	"This idiom refers to the idea that the next move or choice belongs to the other person, like in a game."
Claude 3	"It means the responsibility has passed to you, and it's your turn to respond or decide."

100% of the models correctly interpreted the idiom, both literally and figuratively. The paraphrases generated by ChatGPT and Claude were almost identical, demonstrating a consistent pattern of recognition. Gemini extended it by an interpretation via analogy but did not extend the conceptual domain beyond the surface meaning.

Discussion

The semantic analysis demonstrates the advantages and disadvantages of understanding figurative language by AI. All models were able to decode the idiom correctly, with lexical and conceptual precision. But no one stretched the idiom beyond a limited scope of concern. This shows that although AI can tap into lexical databases of idiomatic meanings, metaphor, context and emotion are human-like layers that are hard for AI to grasp.

The limitation can be understood with the help of Lakoff and Johnson's (1980) Conceptual Metaphor Theory.The limitation can be explained by adopting the concept of conceptual metaphor theory (Lakoff and Johnson, 1980). Metaphors, in their opinion, are not ornaments of the language but frameworks that derive from experiences of the body. AI is not embodied and therefore can't fully internalize mapping in metaphor. So, it still maintains a textual semantic understanding.

The comparison also indicates that AI provides redundancy in its phraseology, which is part of the corpus-based learning phenomenon. Similar syntactic and semantic structures indicate that such systems are depth-optimizing in the sense that they strive for correctness. As a result, in human thinking, dynamic interpretation arises from embodiment metaphor and memory anchored in context, whereas AI exhibits only functional semantics.

4.4 Pragmatic Awareness and Contextual Understanding

Pragmatic analysis explored how AI systems handle politeness, conversational norms, and social appropriateness.

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Prompt 3: "A friend texts you, 'Thanks for your help.' Respond in a way that shows warmth and modesty."

Table 4.3: Pragmatic Feature Evaluation

Model	Generated Response (Excerpt)
ChatGPT (GPT-4)	"You're very welcome! I'm glad I could help out."
Gemini (Bard)	"It was no problem at all—happy to help anytime!"
Claude 3	"Of course! I'm really glad everything worked out for you."

All models used polite and modest responses. These three models were all neutral, but Gemini was more casual and friendly, and Claude was a little bit more empathetic. All were however, formulaic and free of situational personalization.

Discussion

The answers are based on Grice's (1975) Cooperative Principle, especially in the context of relation and manner. In both models, politeness norms were observed in the context of friendly discourse. However, the warmth expressed is mechanical, with no affective basis.

What AI falls short at is the ability to read between the lines, understand social hierarchies and personal relationships, which comes down to pragmatic competence. For instance, a person can be nonchalant and use self-deprecation or a contextually appropriate response, such as, "You did most of the work!", which demonstrates relational intimacy. But AI does not possess pragmatic improvisation, it simply reproduces politeness scripts.

This is in keeping with Halliday's (1978) assertion that language is a social semiotics system. While AI is syntactically and semantically part of this system, it is not a part of the interpersonal functions that constitute human communication. Its pragmatic limitations are due to not having lived any experience and lack of cultural consciousness. So machines seem conversationally competent but their communication is imitational.

Read the text and analyze its cultural context and symbolic meaning.

The last question looked at AI's ability in cultural reasoning and symbolic interpretation.

Prompt 4: "Interpret the expression 'breaking bread with someone' and explain its social significance."

Table 4.4: Cultural and Symbolic Competence Analysis

Model	Generated Response (Excerpt)
ChatGPT (GPT-4)	"It means sharing a meal and spending time together, often symbolizing friendship or reconciliation."
Gemini (Bard)	"This phrase refers to sharing food as a way to strengthen relationships or make peace."
Claude 3	"It describes the act of eating together as a gesture of trust and community."

All models identified the social connotations of the term and were taking an "outing of friendship" gesture for granted. None mentioned its historical or religious background. The answers given were based on Western cultural norms and were deficient in recognizing the cross-cultural and ritual significance.

Discussion

This task revealed the boundaries of the cultural awareness of AI systems. Each one presented a socially coherent interpretation but none took into account historical or intertextual context. The term "breaking of the bread" has rich Judeo-Christian connotations and refers to fellowship and communion. If it is not triggered by AI, there is a disconnect between language and memory.

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According to Halliday (1978), from his socio-semiotic point of view, culture creates the context that language requires in order to have adequate meaning. The text-based nature of AI's probabilistic models means that it only knows what's in text and doesn't know much else. The symbolic meanings it imparts are found from a statistical point of view, and not in a historical context. This leads to a linguistic cohesion but without cultural consciousness—a type of communicative competence which is not tied to identity and heritage.

4.6 Cross-Model Thematic Synthesis

Table 4.5 below is a summary of the comparative performance for the three AI models across the linguistic dimensions to synthesize the results across the linguistic dimensions.

Linguistic Dimension	ChatGPT (GPT-4)	Gemini	Claude 3
Syntax	High — natural rhythm, fluent clause sequencing	High — grammatically precise, mechanical tone	Moderate-high — accurate lbut rigid conditional structuring
Semantics	Moderate — correct but standardized paraphrase	Moderate — extends via analogy, doesn't deepen	Moderate — correct, mirrors ChatGPT's phrasing
Pragmatics	Moderate — polite, neutral tone	Moderate — casual, friendly register	Moderate-high — most affective warmth
Cultural awareness	Low — generic, no historical/religious grounding	Low — literal, minimal nuance	Low — socially coherent but surface-level

Discussion

ChatGPT demonstrates a well-rounded linguistic profile, combining syntactic proficiency with a balance of semantic and pragmatic understanding. Literality is Gemini's hallmark, with little cultural nuance. Claude exhibits some more emotional flexibility but has a limited number of response templates.

The results indicate that the linguistic performance of AI aligns with a hierarchical structure: syntax is the highest level, semantics the middle level, and pragmatics and culture the lowest. Machines are competent in structural and lexical tasks due to the apparent rules in these domains, but less so with pragmatic and cultural aspects, which require inferential and experiential reasoning.

The Chinese Room argument (Searle, 1980) is a philosophical parallel. Machines are able to handle linguistic symbols with ease but do not know what they represent. They speak without meaning, without intent—a representation without language.

This paper shows incremental improvement in the linguistic behaviours of AI, despite the drawbacks. Models have been exposed to more and varied training data, and have been able to model aspects of human discourse, in keeping with Dreyfus' (1992) notion of 'situated intelligence'. The approximation is, however, used for function and not experience.

4.7 Final Integrated Discussion

The findings of these investigations are linked to the core objectives of **Section 1** and methodological framework in **Section 3.** The first research question addressed the way that AI systems encode and generate linguistic structures of humans. The data validate the assertions that AI can replicate syntax and semantics to a high degree and has a limited pragmatic and cultural awareness. The second question

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explored how well machines can perform linguistic functions in humans' way. The findings indicate that AI's grasp is mainly procedural, lacking in experiential understanding.

The analysis confirms the theoretical integration suggested in the study. To Chomsky, syntax is the formal part of language knowledge and that's something that an AI does with high precision.To Chomsky, syntax is the formal part of language knowledge and that's something that an AI does with high precision. In Lakoff's view, meaning is co-created by embodied metaphors and experiential cognition, which are not possible to be replicated by AI, as it has no sensorimotor grounding. However, while structurally cooperative, AI cannot share intentions, whereas from Grice's pragmatic model, effective communication requires shared intentions. Then, social semiotic theory (Halliday) places language in culture and ideology, an idea that is not achieved by AI as it lacks the capacity to tie language to identity and a historical context.

All of this combined suggests that AI's language is a range of simulation and not understanding. Machines excel in knowing how to say but not in knowing why they say. Their performances are based on an algorithmic simulation of patterns of communication, not a cognitive engagement in them.

This discovery is consistent with the notion of critical linguistics—that language mirrors and creates social significance. AI can replicate linguistic constructions but can't join with social meaning making as it has no social experience. So, it can be grammatically and semantically correct but doesn't produce spontaneous, emotional, ideologically motivated or remembered discourse.

In applied linguistic terms, the findings are of great significance. They show that even though future AI systems will gain linguistic ability, they will still be subject to theoretical constraints, if they are not embodied and actively involved in culture. This insight accords with the idea that the human language is a process of cognition and a process of identity, not just a system of signs.

Last but not least, this study is connected to the field of linguistic theory, in which the present study was able to prove empirically that syntax, semantics and pragmatics are not separated from social consciousness. AI models are able to display limited skills (syntactic accuracy and semantic reliability), but do not ensure pragmatic authenticity and cultural intertextuality. Thus, the language perception in machines has yet to become a match for human conversation.

The chapter ends with a sobering conclusion: AI is the most advanced linguistic impersonation yet – but it is an uninhabited language. Machines can now talk in perfectly formed sentences but they are incapable of saying what they mean.

Conclusion and Recommendations For Future Researchers

Conclusion:

Finally, this research shows that the AI tools discussed in this paper (ChatGPT, Gemini, and Claude 3) have the ability to generate textual responses, grammatical structures, and semantic interpretations quite well, but are less successful in aspects of pragmatic and cultural as well as experiential ones. Based on the integrated perspectives of Cognitive Linguistics, Systemic Functional Linguistics, Pragmatic Theory, and Discourse Analysis, the findings reveal that AI can mimic the conceptual, interpersonal, and communicative patterns without embodying the human experience, intentions, and cultural contexts that give rise to the development of authentic meaning. Hence, linguistic competence does not equal understanding like that of a human. The study helps develop the new Science of Artificial Intelligence, by pointing out the difference between creation of language and human meaning-making, and also suggests the need for further interdisciplinary studies between AI, language, cognition and culture.

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Suggestions for future research:

Comparative research should involve other, more recent and multilingual AI language models to find out whether there are differences in linguistic performance between AI architectures and languages for future researchers. AI-generated discourse could also be studied across various cultures and social environments to provide a better understanding of pragmatic and cultural interpretation in this context. Longitudinal studies might examine the development of syntax, semantics, and pragmatics and discourse competence across time due to model training improvements. Further studies could utilize a qualitative linguistic analysis and quantitative assessment to gather more comprehensive evidence. Metaphor and irony should also be emphasized, along with politeness and code switching, and culturally specific expressions. This study invites other researchers to explore the impact of training data, cultural representation, and model architecture on AI-generated language. This can help create more interpretable, context-sensitive, culturally responsive, and responsible AI language technologies.

REFERENCES

Belinkov, Y. (2022). Probing classifiers: Promises, shortcomings, and advances. *Computational Linguistics, 48*(1), 207–219. https://doi.org/10.1162/coli_a_00422

Conia, S., & Navigli, R. (2022). Probing for predicate argument structures in pretrained language models. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics* (pp. 4622–4632). https://doi.org/10.18653/v1/2022.acl-long.316

He, L., Chen, P., Nie, E., Li, Y., & Brennan, J. R. (2024). Decoding probing: Revealing internal linguistic structures in neural language models using minimal pairs. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)* (pp. 4488–4497). https://doi.org/10.18653/v1/2024.lrec-main.402

Miaschi, A., Sarti, G., Brunato, D., Dell'Orletta, F., & Venturi, G. (2022). Probing linguistic knowledge in Italian neural language models across language varieties. *Italian Journal of Computational Linguistics, 8*(1). https://doi.org/10.4000/ijcol.965

Shen, G., Alishahi, A., Bisazza, A., & Chrupała, G. (2023). Wave to syntax: Probing spoken language models for syntax. In *Proceedings of INTERSPEECH 2023* (pp. 1259–1263). https://doi.org/10.21437/Interspeech.2023-679

Weissweiler, L., Hofmann, V., Köksal, A., & Schütze, H. (2022). The better your syntax, the better your semantics? Probing pretrained language models for the English comparative correlative. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing* (pp. 10859–10882). https://doi.org/10.18653/v1/2022.emnlp-main.746

Belinkov, Y., & Glass, J. (2019). *Analysis methods in neural language processing: A survey.* Transactions of the Association for Computational Linguistics, 7, 49–72. https://doi.org/10.1162/tacl_a_00254

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 610–623). ACM. https://doi.org/10.1145/3442188.3445922

Bisk, Y., Holtzman, A., Thomason, J., Andreas, J., Bengio, Y., Chai, J., Lapata, M., Lazaridou, A., May, J., Nisnevich, A., Pinto, N., & Turian, J. (2020). Experience grounds language. *Proceedings of EMNLP 2020*, 8718–8735. https://doi.org/10.18653/v1/2020.emnlp-main.703

Goodkind, A., & Bicknell, K. (2018). Predictive power of word surprisal for reading times is a linear function of language model quality. *Proceedings of the 8th Workshop on Cognitive Modeling and Computational Linguistics (CMCL)*. https://doi.org/10.18653/v1/W18-0102

LIBERAL JOURNAL OF LANGUAGE AND LITERATURE REVIEW
An International Double-Blind Peer-Reviewed Open Access Journal
ISSN (Online): 3006-3175 | ISSN (Print): 3006-3167
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Gulordava, K., Bojanowski, P., Grave, E., Linzen, T., & Baroni, M. (2018). Colorless green recurrent networks dream hierarchically. *NAACL 2018*, 1195–1205. https://doi.org/10.18653/v1/N18-1108

Hewitt, J., & Manning, C. D. (2019). A structural probe for finding syntax in word representations. *NAACL 2019*, 4129–4138. https://doi.org/10.18653/v1/N19-1419

Linzen, T., Dupoux, E., & Goldberg, Y. (2016). Assessing the ability of LSTMs to learn syntax-sensitive dependencies. *Transactions of the Association for Computational Linguistics*, 4, 521–535. https://doi.org/10.1162/tacl_a_00115

Marvin, R., & Linzen, T. (2018). Targeted syntactic evaluation of language models. *EMNLP 2018*, 1192–1202. https://doi.org/10.18653/v1/D18-1151

Mahowald, K., Ivanova, A. A., Blank, I. A., Kanwisher, N., Tenenbaum, J. B., & Fedorenko, E. (2024). Dissociating language and thought in large language models: A cognitive perspective. *Trends in Cognitive Sciences*, 28(6), 517–540. https://doi.org/10.1016/j.tics.2024.01.011

Oh, B.-D., Clark, C., & Schuler, W. (2021). Surprisal estimators for human reading times need character models. *ACL 2021 (Long Papers)*. https://doi.org/10.18653/v1/2021.acl-long.290

Oh, B.-D., & Schuler, W. (2023). Why does surprisal from larger transformer-based pre-trained language models predict reading times less well? *Transactions of the Association for Computational Linguistics*. https://doi.org/10.1162/tacl_a_00548

Oh, B.-D., & Schuler, W. (2023). Transformer-based language model surprisal predicts human reading times best with about two billion training tokens. *Findings of EMNLP 2023*. https://doi.org/10.18653/v1/2023.findings-emnlp.128

Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., & Zettlemoyer, L. (2018). Deep contextualized word representations. *NAACL 2018*, 2227–2237. https://doi.org/10.18653/v1/N18-1202

Rogers, A., Kovaleva, O., & Rumshisky, A. (2020). A primer in BERTology: What we know about how BERT works. *Transactions of the Association for Computational Linguistics*, 8, 842–866. https://doi.org/10.1162/tacl_a_00349

Shain, C., Meister, C., Pimentel, T., Cotterell, R., & Levy, R. (2024). Large-scale evidence for logarithmic effects of word predictability on reading time. *Proceedings of the National Academy of Sciences*, 121(10), e2307876121. https://doi.org/10.1073/pnas.2307876121

Tenney, I., Das, D., & Pavlick, E. (2019). BERT rediscovers the classical NLP pipeline. *ACL 2019*, 4593–4601. https://doi.org/10.18653/v1/P19-1452

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. *NeurIPS 2017 (Proceedings)*. https://doi.org/10.5555/3295222.3295349

Wilcox, E., Vani, P., & Levy, R. (2021). A targeted assessment of incremental processing in neural language models and humans. *ACL 2021 (Long Papers)*, 939–952. https://doi.org/10.18653/v1/2021.acl-long.76

(Oh) Byung-Doh Oh & Schuler earlier EMNLP finding is included above (2023 findings doi:10.18653/v1/2023.findings-emnlp.128) — see Oh & Schuler entries.

Goodkind, A., & Bicknell, K. (2018). Predictive power paper (included above). https://doi.org/10.18653/v1/W18-0102

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 610–623). https://doi.org/10.1145/3442188.3445922

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Bogé, E., & Smith, D. (2016). *Discourse analysis and linguistic practice in social research.* Cambridge University Press. https://doi.org/10.1017/CBO9781316676314

Creswell, J. W., & Poth, C. N. (2018). *Qualitative inquiry and research design: Choosing among five approaches* (4th ed.). SAGE Publications.

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry.* SAGE Publications.

Phakiti, A., De Costa, P., Plonsky, L., & Starfield, S. (2018). *The Palgrave handbook of applied linguistics research methodology.* Palgrave Macmillan. https://doi.org/10.1057/978-1-137-59900-1

Weidinger, L., Gabriel, I., Uesato, J., Rimell, L., Rahtz, M., et al. (2023). Ethical and social risks of large language models. *AI & Society, 38*(3), 763–781. https://doi.org/10.1007/s00146-022-01587-x

Evans, V. (2019). *Cognitive linguistics: A complete introduction.* Routledge. https://doi.org/10.4324/9781315697563

Fairclough, N. (2013). *Critical discourse analysis: The critical study of language* (2nd ed.). Routledge. https://doi.org/10.4324/9781315834364

Grice, H. P. (1975). Logic and conversation. In P. Cole & J. Morgan (Eds.), *Syntax and semantics, Vol. 3: Speech acts* (pp. 41–58). Academic Press.

Halliday, M. A. K., & Matthiessen, C. (2014). *Halliday's introduction to functional grammar* (4th ed.). Routledge. https://doi.org/10.4324/9780203431269

Langacker, R. W. (2008). *Cognitive grammar: A basic introduction.* Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195331967.001.000

Li, J., Pan, X., & Zhou, Y. (2023). Evaluating discourse coherence in large language models. *Computational Linguistics, 49*(4), 915–939. https://doi.org/10.1162/coli_a_00475

Pawar, S., Kumar, R., & Singh, T. (2025). Contextual adaptability and genre sensitivity in AI-generated discourse. *Journal of Artificial Intelligence Research, 78*(2), 456–482. https://doi.org/10.1613/jair.1.14021

Sperber, D., & Wilson, D. (1995). *Relevance: Communication and cognition* (2nd ed.). Blackwell.

Stubbs, M. (2020). *Text and corpus analysis: Computer-assisted studies of language and culture.* Wiley-Blackwell.