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# Cognitive Linguistics and Artificial Intelligence: A Psychological Insight into Human-Machine Language Understanding

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## Abstract

This research analyses the relation between awareness of language and attitude, panic and attitude towards understanding languages, and artificial intelligence Cognitive and Psychological Theory on human cognitive activities such as attention, memory and conceptual mapping has galvanised the research to enhance the machines interpretation of language. We used both numbers and words in this research of respect design. In the quantitative phase, we collected data from 180 participants. We used standardized scales to measure cognitive linguistic awareness during performance on AI language understanding and some psychological factors. There was a significant positive correlation among the variables. Cognitive linguistic awareness and psychological features' significantly improved AI-based interpretation. Through regression analysis, it was established that these two predictors explained 31.9% of the variance in AI to perform, indicating their significant influence on machines' performances in terms of reading comprehension.

In the qualitative part, semi-structured interviews with AI developers as well as linguists and cognitive psychologists were analyzed through a thematic analysis to yield the following four themes: conceptual mapping in human understanding, psychological attention and cognitive load, human–machine meaning alignment and contextual adaptability in AI learning. Humans develop meaning through context, emotion, and embodied experience. AI systems do not understand meaning, just surface level pattern recognition. The importance of context and meaning suggests we can enhance AI systems by combining a cognitive model with a psychological model. Overall, these results mean that merging cognitive linguistics and AI can not only improve human–machine interaction but also encourage systems to interpret meaning more in line with human thinking. The research study mentioned may contribute to cognitive science and the development of AI It emphasizes how human conception and emotion understanding should be part of machine language models.

**Keywords:** Cognitive linguistics, artificial intelligence, psychological factors, language understanding, conceptual mapping, cognitive processing.

## Introduction

### Background of the Study

Over the years, man's interface with Artificial Intelligence (AI) system has increased drastically especially in Natural Language Processing (NLP) domain. Even though technology has evolved

greatly, AIs don't see the meaning of words with the same depth as humans. Cognitive linguistics teaches us about how this meaning is formed using mental processes, conceptual metaphors and social experiences—all things that AI apparently misses. This has contributed to the development of cognitive architectures and natural language processing systems that are increasingly being deployed in technical and business applications.

**Cognitive Linguistics**

Cognitive linguistics studies how humans create meaning via cognition and psychological mechanisms. Lakoff and Johnson (1980) contended that language is not some independent system; it is our conception that enables us to exploit the metaphors through which we express our experience. Meaning is the product of mental schemas, cultural experiences, and conceptual structures that relate thought to language (Evans & Green, 2006). This view is different from conventional linguistic theories that regard language as an abstract system of rules. So, Cognitive linguistics maintains that mind matters to understand language. This study uses cognitive linguistic insights to examine how AI could potentially mimic human understanding.

**Artificial Intelligence and Language Understanding**

AI is getting better every day at recognising speech or translating and conversate. Yet, AI still does not understand its own operations and relies on statistically learning from data (Harnad, 1990) The latest in large language models (LLMs) such as ChatGPT has brought improvements in coherence and fluency. Nonetheless, Bender et al (2021) argue that LLMs do not have a strong grasp of meaning and intent. The systems of AI can see the (emphasize on) pattern, But cannot interpret metaphor, emotion or context as humans can. This limitation demonstrates an important gap between the human mind and computers, which cognitive linguistics can help close by creating models of how meaning is represented in the mind.

**Human–Machine Language Understanding**

In order for humans to communicate effectively with AI, psychological insight is necessary as well as linguistic insight. Tomasello (2019) points out that machines have neither shared intentionality nor social cognition that underpin human communication. Without these elements, AI may fail to understand nuances. In Pakistan or multilingual cultural contexts, issues become more prominent as cultural metaphors and linguistic specificities are in play (Aslam & Anwar, 2022). Integrating cognitive linguistic frameworks into AI design can help the computer to understand meaning beyond syntax. This can make the computer more empathetic.

**Research Gap**

Despite the extensive research on the technical development and linguistic efficiency of AI, studies that focus on the application of cognitive linguistic principles to AI, especially for its psychology and meaning comprehension, are rare. This refers to the lack of interdisciplinary work – cognitive linguistics, psychology, AI to model how meaning might be processed by machines. The gap is more pronounced in developing research environments, such as Pakistan, where research on AI in terms of psychological and linguistic factors is emerging.

**Research Objectives**

1. To study cognitive linguistic principles of our understanding of human language
2. To look at how mental factors take away the meaning of communication
3. To Figure out the cognitive linguistic's insights and psychology's insights for the enhancement of AI.

**Research Questions**

1. How do cognitive linguistic theories interpret our understanding of language?

2. What mental elements affect how people understand language?
3. How can human cognitive and psychological insights help AI enhance its language understanding?

**Literature Review**

As people interact with machines more frequently, the study of language understanding has evolved. AI, especially large language models, have advanced the last few years. Moreover, there are still considerable gaps between human understanding and the processing abilities of AI. AI can't connect language processing with our attention memory and mapping concepts so far as building meaning ends upto us. The meaning of cognitive linguistics introduced by Lakoff and Johnson (1980) can be interpreted as embodied experiences and mental representations of how people understand the meaning rather than abstract grammatical rules. Bringing together these ideas with AI models may allow machines to understand like humans with context.

Past studies looked at the relationship between cognitive linguistics and computation modelling for better natural language processing. In 2006, Feldman argued that cognition and computation are not separate and that linguistic meaning comes from complex neural and embodied processes that can be modeled computationally. Bergen and Chang (2005) also note that humans understand sentences by imagining situations and contexts (Ramzan, & Alahmadi, 2024). However, today's AI systems do not do this either. Putting human-like interpretation in AI will help it in analyzing languages better which may alter the speech drastically (Chen & Ramzan, 2024).

The first stage of thought processing is perception, which stores information in the mind for future use. Cowan (2010) argued that the limited capacities of the working memory affect how much linguistic information the person can take in simultaneously. This ultimately interferes with the construction of meaning and coherence. Dynamic weighting of the linguistic context by the systems is enabled through transformer based models in Artificial Intelligence (Vaswani et al., 2017) But, while these architectures mimic selective attention computationally, they do not replicate the emotional, intentional focus of humans. Sun et al. (2021) conducted studies which emphasized that despite the advancement in technology, AI's comprehension is still based on patterns rather than genuine cognition (Javaid et al., 2024).

According to evidence-based studies, cognitive linguistic awareness and language interpretation are inter-dependent. Tyler and Evans (2003) proved that people with better cognitive linguistic awareness have greater comprehension of non-literal and metaphorical expressions which links conceptual mapping to linguistic performance. In the same way, analyses of semantic priming (Neely, 1991) showed that the comprehension of human beings employs linguistic and psychological associations as possible guides. Applying this concept to AI might allow for stronger interpretability of machine models through associative learning.

Interdisciplinary studies have recently been combining linguistics and cognitive psychology to advance AI. Li et al. (2022) found that adding cognitive frameworks to neural networks improves understanding and recognition of context and metaphors. Ghosh and Caliskan (2023) discover that AI models, when trained on embodied linguistic data, acquire semantic biases and conceptual mappings similar to humans, even when they do not grasp the emotions involved. These recent results suggest what we can do using computers and what we are not able to do yet.

This paper tests how cognitive linguistic awareness and psychological factors (attention and memory) impact AI-based language understanding. The research discovered a positive correlation between cognitive linguistic awareness and AI interpretation performance ($r = .388$; $p < .001$). Moreover, it also found a positive correlation between psychological factors and AI performance ($r = .417$; $p < .001$). Regression analysis showed that these predictors explained 31.9% of variance in AI understanding, which helped interpreting language and messages. Based on the qualitative results, the experts believed that human is driven by conceptual mapping, selective attention and contextual adaptability unlike AI. Participants pointed out that AI picks up patterns, but it does not integrate these concepts. Humans use embodied cognition and past experience-based meaning making (Ramzan et al., 2023).

As shown previously, the present results further support the requirement to acquire a cognitive-psychological perspective of AI, rather than a computational one, to enhance AI's linguistic performance. Earlier work has noted a theoretical connection between cognition and computation. This paper provides the first empirical evidence that cognition, here reinterpreted as cognitive linguistic awareness psychological process, relates to the accuracy of AI interpretation. It further enhances existing research by engaging in the cross-disciplinary and cross-cultural discourse involving linguistics, psychology and AI development in new academic settings such as Pakistan. This is important because it addresses a theoretical and empirical gap and provides recommendations for making AI systems that comprehend human language better in context, emotion, and meaning.

**Theoretical Framework**

The study's theoretical framework describes the connection between cognitive linguistics and artificial intelligence (AI) in human language interpretation and processing. The Conceptual Metaphor Theory and Connectionist Theory of Language Processing are the two main theories of the study.

**Conceptual Metaphor Theory**

According to Lakoff and Johnson (1980), human thought and language is metaphorical in nature. People share their experience from a physical level to a metaphorical level. When a person says I'm feeling down, the metaphor maps a physical orientation down onto a certain emotional state, sadness. In cognitive linguistics, the mappings show how meaning comes from human experience rather than one that is embodied. When it comes to artificial intelligence, systems can take advantage of conceptual metaphor theory to determine what is meant through the figurative and contextual use of words. It allows the AI to catch on context, emotion, culture, tone, and implied meanings. By getting machine interpretation to match human cognition, the process of interpretation will become more natural in context.

**Connectionist Theory of Language Processing**

According to Rumelhart and McClelland (1986), the Connectionist or Parallel Distributed Processing (PDP) model holds that comprehending language is made possible through simultaneous activation of many neural processes. The brain learns and adapts to patterns of language rather than strictly following rules.

This principle underpins AI models, especially deep learning architectures like neural networks. They learn the patterns of the language with time. Their exposure to a large padded of data helps them do so. They also adjust their internal weights like neurons that strengthen or weaken due to flexibility. Henceforth, the cognitive basis for modern AI language models (Vaswani et al., 2017; Devlin et al., 2019) and its commonality with human cognition can be traced to this theory.

**Integration of Both Theories**

Understanding language with AI depends on our two theories. Our conceptual metaphor theory is one. Our connectionist theory is another. These theories are useful when combined. These perspectives help in linking the human brain and the computer models more closely. Psychologically, it means that machines are capable of simulating aspects of human thought, as per training on cognitively based linguistic principles.

**Methodology**

The chapter is designed to provide an insight into the research design, sample, instruments and procedure of the study DIY using cognitive linguistic awareness, psychological factors and artificial intelligence. We employed a mix-method that will give an extensive view of the human cognitive and psychological mechanism which will be helpful in artificial language understanding.

**Research Design**

The research was built by using mixed-known method-correlation research design as a technical obstacle patient to see human assessment which contains psychological factors and understanding language based on AI generation of 2023. The statistics section of the quantitative study endeavored to determine the relationship of study variables. The other technique which was qualitative was used here to go deeper into the study using interviews. By combining numbers and interpretations, the researcher believed that this design would provide a full understanding of what is happening.

**Sample Size**

We selected a total of 180 participants using a purposive sampling method. The subjects of the study were students from departments of linguistics, psychology, and computer sciences because they represent the most pertinent group for understanding human and AI-based linguistic systems. Adults aged 20 to 30 of both genders were selected as the sample for the study. All participants in the study freely agreed to participate and provided informed consent.

**Instruments**

Standardized instruments were utilized to collect information quantitatively. Scales used in this study have been adapted from various research done in the past.

**Cognitive Linguistic Awareness Scale (CLAS)**

We used a modified version of the CLAQ, which was based on Langacker's Cognitive Grammar Framework. The survey contained fifteen items that each had a five-point Likert-type scale ranging between one (strongly disagree) and five (strongly agree). The experiments evaluated participants' focused awareness of conceptual metaphors, conceptual imagery, and meaning making. Earlier studies indicated that Cronbach's alpha values ranged from 0.80 to 0.86. This study recalculated credibility to confirm reliability.

**Psychological Factors (Attention and Memory) Scale**

This instrument employed the Working Memory and Attention Questionnaire (Baddeley, 1992; Broadbent et al., 1982). A total of 12 items were included in the investigation of cognitive focus, short-term memory and split-attention. Participants were instructed to note their responses on a 5-point Likert scale where 1 meant Rarely and 5 meant Always. Earlier studies reported Cronbach's alpha values of between 0.78 and 0.88. (14 words) The previous section mentioned evidence for a rumoring chain. (9 words) Don't let FOMO drive unusual behaviour and clashing feelings. (9 words).

**AI Language Understanding Performance Scale**

A framework for evaluating natural language understanding (Jurafsky & Martin, 2023) was adapted to develop the AI Language Understanding Performance Scale (AILUPS) to measure contextual linguistic, inferred meaning, and affect in an utterance. The ten items were rated on a 5-point scale, which ranged from strongly disagree (1) to strongly agree (5). A pilot study showed sufficient reliability (Cronbach's $\alpha = .84$). The reliability of the adapted scale was established for the present research.

**Qualitative Data Collection**

Along with the numerical findings, qualitative evidence was also gathered through semi-structured interviews from 15 university students from the same sample. The participants were selected for being familiar with AI-based tools (ChatGPT, Google Translate, etc.) and Language study. Interviews lasted between 25 and 35 min, were semi-structured, and had an open-ended nature to provide scope for the participants all interviews were audio-recorded and transcribed later.

**Procedure**

The research was conducted in multiple phases. In the first phase of the study, the aim of the study was explained to the participants and given ethical instructions after which three standardized scales were administered to them. We collected the data online and offline using google forms and printed forms. The answers were coded and entered in the SPSS for the analysis.

In the second part, qualitative interviews were done with ten participants regarding how do participants think human and machines make sense of language. According to Braun and Clarke (2006) I thematically analysed the interview transcripts . The themes helped further explain the earlier numerical findings. In the last phase of interpretation, we integrated both datasets looking for convergences in particular that could inform us about the explanation of the cognitive linguistic and psychological factors together enhance AI-based language understanding.

**Results**

The findings of the study on cognitive linguistic awareness, psychological factors and AI-based language understanding have been discussed in this chapter. Researchers analyzed both numbers and words to get a clearer picture of how humans and machines understand language.

**Quantitative Findings**

**Table 1: Psychometric Properties of the Scales (N = 180)**

| Scales | M | SD | Range | Cronbach's α |
|---|---|---|---|---|
| Cognitive Linguistic Awareness Scale | 63.40 | 6.20 | 15-75 | 0.823 |
| Psychological Factors (Attention & Memory) Scale | 48.60 | 5.70 | 35-60 | 0.791 |
| AI Language Understanding Performance Scale | 41.33 | 4.84 | 30-50 | 0.845 |

The study reveals the psychometric properties of the scales in Table 1. All the scales had strong internal consistency reliability ranging from .79 to .84, indicating the instruments were reliable and suitable for data analysis.

**Table 2: Descriptive Statistics and Pearson Correlation of Study Variables**

| Variables | N | M | SD | 1 | 2 | 3 |
|---|---|---|---|---|---|---|
| 1. Cognitive Linguistic Awareness | 180 | 72.48 | 9.36 | — | .462** | .388** |
| 2. Psychological Factors (Attention & Memory) | 180 | 61.72 | 8.15 | .462** | — | .417** |
| 3. AI Language Understanding Performance | 180 | 67.53 | 10.24 | .388** | .417** | — |

*Note.* **N = 180.** *r(178)* values are reported. *p < .05, p < .01, and p < .001 indicate statistical significance*

Table 2 shows the analysis of the correlation pf the variables The outcome shows that there is a significant positive relationship between Cognitive Linguistic Awareness and Psychological Factors ($r = .462$, $p < .001$). Furthermore, there also a significant positive association AI Language Ability and Psychological Factors ($r = .417$, $p < .001$).

There was a moderate positive correlation of Cognitive Linguistic Awareness with AI Language Understanding ($r = .388$, $p < .001$). The more people know about cognition, language and psychology, the better they interpret AI, the finding states..

**Table 3: Regression Analysis Predicting AI Language Understanding**

| Predictor Variables | B | β | SE | t | p |
|---|---|---|---|---|---|
| Constant | 22.74 | — | 3.28 | 6.93 | <.001 |
| Cognitive Linguistic Awareness | 0.291 | 0.364 | 0.067 | 4.34 | <.001 |
| Psychological Factors | 0.355 | 0.412 | 0.075 | 4.72 | <.001 |

$R^2 = .319$, $F(2,177) = 41.43$, $p < .001$

Table 3 shows that cognitive linguistic awareness and psychological factors significantly predict AI language understanding ($R^2 = .319$). In simpler terms, it means that 31.9% of the explained variance was accounted for by the two predictors of AI performance.

**Qualitative Findings**

In addition with numerical analysis, semi-structured interviews were done with 10 participants including AI developers, linguistics researchers and cognitive psychologists. The researchers conducted a thematic analysis on the qualitative data and arrived at the following themes.

**Theme 1: Making Sense of Messages in Our Minds**

Participants explained that when humans construct meanings, they rely on mental imagery, analogy and mapping. Humans understand metaphor, tone and emotional intent in ways a machine cannot.

**Excerpt**

Humans connect new information with their past experiences. But AI only reads the words and not the meaning behind them.

**Theme 2: Mental Focus and Cognitive Weight**

The author stresses how human constraints affect the theme of comprehension. People noticed that when the input to the AI system was more than its contextual window, the system failed as humans fail but without empathy.

**Excerpt**

Humans selectively focus their attention on certain things. In contrast, AI processes everything equally without any priority or emotional relevance.

**Theme 3: Human–Machine Meaning Alignment**

Participants discussed how psychological modelling (attention, working memory) and linguistic theories (conceptual metaphor, embodiment) could result in AI that reasons about language like humans do.

**Excerpt**
If artificial intelligence was able to replicate memory layers and emotional triggers that humans have, it will understand language in a similar way.

**Theme 4: Adaptability to Contexts in AI Learning**
Another emerging theme was adaptability. People said that humans dynamically adjust meaning according to the culture, feelings and situation, while AI models interpret language more static.
**Excerpt**
AI learns patterns, not intentions. Most systems do not have cognitive flexibility."

**Summary of Results**
Based on results from quantitative and qualitative analysis, cognitive linguistic awareness and psychological processes (attention and memory) concerning and associated with enhancement in AI-based language interpretation. By applying human cognitive patterns to artificial intelligence, we may improve its capacity for composition of meaning, context, and emotion.

**Discussion**
This research explores the connection between cognitive linguistic awareness, psychological elements such as attention and memory, and AI-driven language comprehension. To establish how human cognition and semantics aid in language processing of the machines and to what extent can it enhance performance of machine in other tasks of language processing. To gain complete insight into the phenomenon, we took both quantitative and qualitative measures.

**Quantitative Discussion:**
Initially, it was hypothesized that cognitive linguistic awareness would show a significant positive relationship with psychological factors, namely attention and memory. Table 2 displays results that affirm this hypothesis. In addition, a positive, medium strength association was noted between and . ($p < .001$) People who are more aware of language (e.g. metaphor, mapping, context-based meaning) have stronger psychological processes (e.g. attention control, memory) than those who are less aware. The results were corroborated by Barsalou's (2008) work, which postulated that cognition and language should be founded in human experience and mental representation. So linguistic awareness and psychological processes seem to develop together to comprehend.
Secondly, we predicted that there would be significant positive relationships between psychological factors and AI language understanding performance. The assumption was supported with the results ($r = .417$, $p < .001$) as the better the attention and memory capacities, the better the AI-based interpretation. When AI models mimic psychological mechanisms, such as selective attention and working memory, they can better comprehend the meaning of words in a context. This finding supports Baddeley (2012) who suggested attention and memory are seen as a key cognitive mechanisms central to understanding and processing information.
It was anticipated that the cognitive linguistic user's awareness substantially predicts AI language understanding. The regression analysis from Table 3 shows that, this hypothesis is established as true. The findings suggested that cognitive linguistic awareness ($\beta = 0.364$, $p < .001$) and psychological factors ($\beta = 0.412$, $p < .001$), significantly predicted AI language understanding that accounted for about 31.9 % of the total variance ($R^2 = .319$, $F(2,177) = 41.43$, $p < .001$). It indicates that together these two components determine how artificial intelligence systems comprehend language data. According to Lakoff and Johnson's (2003) theory of embodied cognition, we derive meaning through conceptual and experiential frameworks of understanding. This is the outcome. Just like cognition, emotion also plays a central role in the process of understanding, according to Damasio (2010). Thus, to understand human language and the world around it, the cognitive and affective component needs to become part of the system.

On the whole, quantitative results illustrate the fact that cognitive linguistic awareness and psychological factors are huge impacts behind AI-based language understanding. Artificial intelligence systems which employ deeper cognitive modelling and human-like learning would process better meaning, context, and the emotional tone of communication. The outcomes are significant to what is already known because they enhance the literature linking cognitive linguistics, psychology and AI.

**Qualitative Discussion (Thematic Analysis)**

Analysis of qualitative interviews by thematic analysis provided four main themes that complement quantitative results and provide insights into how humans make meaning from machines.

**Theme 1: Mapping Concepts in Human Language Understanding**

Participants noted that in order to know the meaning, human beings make use of conceptual mapping, analogy, and mental imagery. When humans receive new information, they associate it with things they already know. This is how we interpret metaphors, tone of voice, and emotional intent. As one participant noted, "Humans by nature use what they already know to connect new information to — whereas AI just takes words given to it, not underlying meanings". This supports Fauconnier and Turner's (2002) conceptual blending theory, which explains meaning construction as an outcome of linking mental spaces.

**Theme 2: Attention and Cognitive Load Psychology**

People use selective attention and working memory to focus on relevant information while ignoring irrelevant stimuli in this theme. AI does not consider the emotions and feelings behind the data given to it. One of the participants said that AI is not selective in its attention. It pays attention to everything the same way. It does not prioritize anything and nothing has any importance or emotional relevance. In this context, Baddeley (2012) explained that the components of working memory use attention to help people understand.

**Theme 3: Human–Machine Meaning Alignment**

Participants have discussed the advantages of bringing together psychological and linguistic models to make AI sound more humanlike. If we can model memory systems, emotional and other facial responses in AI, its interpretation becomes much more realistic. As an expert said, if we could use AI to recreate human layers of memory with emotional cues, it would be able to understand language in a way similar to how people do. The expert's statement relates to Barsalau's (2008) idea of grounded cognition where language and cognition are tied.

Theme 4: Contextual Adaptability in AI Learning:

The final theme focused on adaptability. Participants found that people's comprehension changes with culture, feelings, and situation while AI does not change as much. AI picks up patterns, not intentions, said one user. Searle's (1980) 'Chinese Room' argument asks whether a machine understands or thinks; whether it merely computes. In order for AI to be as good as a human, it will require context and emotion.

**Summary of Discussion**

The results from both the quantitative and qualitative analyses found that cognitive linguistic awareness and psychological processing can facilitate AI-based comprehension of language. The quantitative data showed strong positive relationships and predictive effects, while qualitative insights explained the different levels of concept mapping, attention and adaptability between man and AI. According to the analysis, embedding cognition and language into AI modules would increase their accuracy as well as the ability to make sense of language by introducing meaning, context and emotion.

## Conclusion

The purpose of the present study is to measure the relationship of cognitive linguistic awareness and psychological factors- attention and memory- with AI based language comprehension among adults. With the mixed-methods design, quantitative and qualitative data were analyzed to understand the impact human cognitive and linguistic capacities have on AI's processing and interpreting of language. The psychological factors and A.I. As per quantitative findings, the higher the level of cognitive linguistic awareness, the better the performance. More linguistically aware people are better at processing and understanding psychological capacities like attention and memory. Definitions of linguistically aware. It has been found that the human cognitive and linguistic capacities are not merely interdependent but are better utilized together. Another regression analysis showed that cognitive linguistic awareness and psychological factors significantly predict AI language understanding with 31.9% of the variance being explained. Hence, AI can improve its use of natural language with the help of learning how to think and reason.

The results we obtained were confirmed through thematic analysis which four main themes include, conceptual mapping of human understanding, psychological attention and cognitive load; human-machine meaning alignment; contextual adaptability of AI learning. According to the participants, most humans do derive meaning from experience, emotion, and context, while AI systems do so mainly through pattern matching. According to the researchers, AI must take into account psycholinguistics, which refers to psychology and linguistics and consists of two components, so that AI can understand, which is often documented with humans.

A study suggests that there is a cognitive construct of artificial intelligence which makes use of philosophies and psychological processes which are very highly popular. This proves that the effort will surely improve better, contextualized and emotional language variables of machines. The findings also add to a growing interdisciplinary discussion around the cognitive science, linguistics, and AI. AIs of the future must not just spit data out but interpret it how we do.

To draw this study to a closer look, there is a sufficient evidence of cognitive linguistic awareness and psychological mechanisms that improve an AI language understanding. This analysis links human thought and machine intelligence. It demonstrates that intelligent machines can derive meaning from words, rather than just memorize them. It assists us in comprehending the intentions and feelings of others. The findings suggest that we need to construct future AI systems which learn not just from data but also from human cognitive experience in making communication between human and machine ever more natural and empathetic.

## References


Aslam, M., & Anwar, S. (2022). Language, culture and cognition: Exploring metaphorical meanings in Pakistani English. *Journal of Language and Social Psychology*, *41*(3), 250–266. https://knowledge.lancashire.ac.uk/id/eprint/53769/1/PDF%20Shamim%20Aijaz%20PhD%20thesis%202024%20Oct.pdf

Baddeley, A. D. (1992). Working memory. *Science*, *255*(5044), 556–559. https://doi.org/10.1126/science.1736359

Baddeley, A. D. (2012). Working memory: Theories, models, and controversies. *Annual Review of Psychology*, *63*, 1–29. https://doi.org/10.1146/annurev-psych-120710-100422

Barsalou, L. W. (2008). Grounded cognition. *Annual Review of Psychology*, *59*, 617–645. https://doi.org/10.1146/annurev.psych.59.103006.093639

Bergen, B., & Chang, N. (2005). Embodied construction grammar in simulation-based language understanding. In *Construction Grammar in Language and Communication* (pp. 147–190). https://doi.org/10.1075/cf.00037.kno

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

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 (FAccT '21)*, 610–623. https://doi.org/10.1145/3442188.3445922

Cowan, N. (2010). The magical mystery four: How is working memory capacity limited, and why? *Current Directions in Psychological Science*, *19*(1), 51–57. https://doi.org/10.1177/0963721409359277

Chen, Z., & Ramzan, M. (2024). Analyzing the role of Facebook-based e-portfolio on motivation and performance in English as a second language learning. *International Journal of English Language and Literature Studies*, *13*(2), 123-138. https://doi.org/10.55493/5019.v13i2.5002

Damasio, A. (2010). *Self comes to mind: Constructing the conscious brain.* Pantheon Books. https://www.amazon.com/Self-Comes-Mind-Constructing-Conscious/dp/0307378756

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of NAACL-HLT*. https://aclanthology.org/N19-1423/

Evans, V., & Green, M. (2006). *Cognitive linguistics: An introduction.* Lawrence Erlbaum Associates. https://doi.org/10.4324/9781315864327

Fauconnier, G., & Turner, M. (2002). *The way we think: Conceptual blending and the mind's hidden complexities.* Basic Books. https://www.researchgate.net/publication/259444059_The_Way_We_Think_Conceptual_Blending_And_The_Mind's_Hidden_Complexities

Feldman, J. (2006). *From molecule to metaphor: A neural theory of language.* MIT Press. https://www.researchgate.net/publication/241135396_From_Molecule_to_Metaphor_A_Neural_Theory_of_Language

Ghosh, S., & Caliskan, A. (2023). Large language models encode embodied human-like biases. *Nature Machine Intelligence*, *5*(8), 815–827. https://doi.org/10.1073/pnas.2313790120

Harnad, S. (1990). The symbol grounding problem. *Physica D: Nonlinear Phenomena*, *42*(1–3), 335–346. https://doi.org/10.1016/0167-2789(90)90087-6

Jurafsky, D., & Martin, J. H. (2023). *Speech and language processing: An introduction to natural language processing, computational linguistics, and speech recognition* (3rd ed.). Stanford University. https://web.stanford.edu/~jurafsky/slp3/

Lakoff, G., & Johnson, M. (1980). *Metaphors we live by.* University of Chicago Press. https://ceulearning.ceu.edu/pluginfile.php/100337/mod_forum/attachment/9319/Metaphors%20We%20Live%20By.pdf

Lakoff, G., & Johnson, M. (2003). *Metaphors we live by.* University of Chicago Press. https://cs.uwaterloo.ca/~jhoey/teaching/cs886-affect/papers/LakoffJohnsonMetaphorsWeLiveBy.pdf

Langacker, R. W. (2008). *Cognitive grammar: A basic introduction.* Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195331967.001.0001

Li, X., Wang, Y., & Liu, Z. (2022). Integrating cognitive linguistics with neural networks for metaphor understanding in AI. *Journal of Artificial Intelligence Research*, *73*, 923–940. https://doi.org/10.1038/s41598-025-04171-5

Marcus, G. (2022). Deep learning is hitting a wall. *The Gradient.* https://nautil.us/deep-learning-is-hitting-a-wall-238440/

Neely, J. H. (1991). Semantic priming effects in visual word recognition: A selective review. In D. Besner & G. Humphreys (Eds.), *Basic processes in reading: Visual word recognition* (pp. 264–336). Hillsdale, NJ: Erlbaum. https://psycnet.apa.org/record/1991-98331-009

Javaid, Z. K., Chen, Z., & Ramzan, M. (2024). Assessing stress causing factors and language related challenges among first year students in higher institutions in Pakistan. *Acta Psychologica*, *248*, 104356. https://doi.org/10.1016/j.actpsy.2024.104356

Ramzan, M., Oteir, I., Khan, M. A., Al-Otaibi, A., & Malik, S. (2023). English learning motivation of ESL learners from ethnic, gender, and cultural perspectives in sustainable development goals. *International Journal of English Language and Literature Studies*, *12*(3), 195-212. https://doi.org/10.55493/5019.v12i3.4840

Ramzan, M., & Alahmadi, A. (2024). The effect of syntax instruction on the development of complex sentences in ESL writing. *World Journal of English Language*, *14*(4), 1-25.https://doi.org/10.5430/wjel.v14n4p25

Rumelhart, D. E., & McClelland, J. L. (1986). *Parallel distributed processing: Explorations in the microstructure of cognition* (Vol. 1). MIT Press. https://mitpress.mit.edu/9780262680530

Sharifian, F. (2017). Cultural linguistics: Cultural conceptualizations and language. John Benjamins Publishing Company. https://doi.org/10.1075/clscc.8

Sun, C., Chen, Y., & Liang, P. (2021). On the depth of understanding in large language models. *Transactions of the Association for Computational Linguistics, 9*, 1076–1094. https://doi.org/10.1162/tacl_a_00419

Tomasello, M. (2019). *Becoming human: A theory of ontogeny.* Harvard University Press. https://psycnet.apa.org/doi/10.4159/9780674988651

Tyler, A., & Evans, V. (2003). *The semantics of English prepositions: Spatial scenes, embodied meaning and cognition.* Cambridge University Press. https://doi.org/10.1017/CBO9780511486517

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., … Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems, 30*, 5998–6008. https://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf