Frontiers in Global Research

ISSN: 3107-5398
Volume 1, Issue 3, Sep-Oct 2025, pp. 14-16
Journal homepage: *https://fgrjournal.com*

Review Article

Conversational Implicature in Human-AI Interactions: A Pragmatic Perspective

Yousif Ali Yousif Salman[1], Doaa Taher Matrood[2]*

Assistant Lecturer, Department of English, College of Human Sciences, University of Diyala, Diyala, Iraq

ARTICLE INFO

Keywords:
Conversational implicature, human-AI interaction, pragmatics, Gricean maxims, discourse analysis

Article History:
Received: 11-08-2025
Accepted: 15-09-2025
Published: 4-10-2025

ABSTRACT

AI (artificial intelligence) systems should be able to talk more and more like people as the way people use computers changes. But there is still a big problem: how to understand and use verbal implicature, which is a key part of being pragmatically competent. This article looks at how implicature works between people and AI, as well as how well AI systems understand and use suggested ideas. From the point of view of Grice's Cooperative Principle and maxims, this study looks at how well chatbots like ChatGPT, Google Assistant, and Siri work in real life. There is a mix of different research methods used in this paper, such as controlled tests and qualitative speech analysis. It also looks at how people understand implicature and how AI acts in various situations, such as when it needs to be funny, polite, or use subtle language. This study utilises various aspects of language to demonstrate that AI can replicate some meanings after being trained on large datasets, but it often struggles to comprehend non-literal purposes or process contexts dynamically.

Cite this article:
Salman, Y., & Matrood, D. (2025). Conversational Implicature in Human-AI Interactions: A Pragmatic Perspective. *Frontiers in Global Research*, *1*(3), 14-16. https://doi.org/10.55559/fgr.v1i3.22

1. Introduction

How people and computers talk to each other has changed as artificial intelligence (AI) has grown. As time goes on, conversational AI is used more and more in regular life, from computer helpers to customer service robots. AI systems can do amazing things with words, but they still have trouble with pragmatic ability, which is one of the trickiest parts of language. A lot of people think that pragmatics, the study of how people use words in different settings, is less important than they think. In this area, conversational implicature, which means that meaning is implied instead of being said clearly, is very important.

People who speak human language often use implication to be nice, funny, or mean without saying it directly. For instance, saying "It's getting late" can mean that you want to end the talk. Based on his Cooperative Principle and verbal maxims, Grice's theory of implicature (1975) explains how people figure out these kinds of meanings. People can easily figure out what an implied meaning means because they share cultural and social knowledge. But AI systems, which look at language data statistically, often miss these subtle clues.

This study looks into how conversational implicature works in conversations between humans and AI. It looks at things like, "How well do AI systems recognize and create implicature?" How hard is it for AI to handle these kinds of implicatures? How do people think about implicatures made by AI compared to those made by humans? These questions are important and timely, especially as AI moves into areas that need sensitive, caring, or socially acceptable answers.

The paper starts with some basic ideas in pragmatics and implicature. It then goes on to look at some new research in AI language creation and conversation processing. Then it shows case studies of how AI interacts with people, using both known datasets and brand-new conversational situations made to test certain implications. Through this view, the study gives important information about the pros and cons of current AI conversation systems and suggests ways to improve realistic understanding in AI contact in the future.

2. Literature Review

H.P. Grice (1975) came up with the idea of "conversational implicature," which is the meanings that speakers imply beyond what they say. Grice's Cooperative Principle, which is made up of four verbal maxims (quantity, quality, connection, and style), shows how people create and understand implicatures. If someone breaks the rule of connection, like saying "The weather is nice" in response to a question about chores, it means they are trying to say something subtly.

Since Grice, many other scholars have added to implicature theory. In 1983, Levinson divided implicatures into two groups: generalized and particularized. Horn (1984) and Sperber & Wilson (1995), on the other hand, focused on relevance and inference processes. Since then, pragmatic theories have influenced computer models that aim to simulate human communication. It is still very hard to incorporate these ideas into AI, though. Early rule-based systems in computer languages tried to describe implicature but had some problems (Allen, 1995). Machine learning and large-scale neural models have made it possible for systems like GPT-3 (Brown et al., 2020) and ChatGPT (OpenAI, 2022) to write text that sounds incredibly natural. However, these

******Corresponding Author*:
yousuf.en.hum@uodiyala.edu.iq *(Salman, Y.)*

models often don't take circumstances into account. Niven & Kao (2019) and Bender & Koller (2020) studies say that language models are good at making sense at the surface level but bad at making sense of functional inferences and roots in the real world.

New discourse-based studies (Shin et al., 2022; Dastjerdi et al., 2023) look at how talking robots deal with implicature in real life. The results show that AIs are only partly successful. They usually get simple indirect speech acts right, but they mess up when it comes to comedy or culturally embedded meanings. For example, AI's politeness tactics, which depend on implicature, don't always work, so it can give answers that seem sudden or wrong (Pérez-Marín & Pascual-Nieto, 2011).

Traum and Allen (1994), for example, say that conversation context and user modeling are very important for understanding implicature. Newer systems in pragmatic annotation, like the ISO 24617-2 standard, try to teach models discourse-level traits, but they are still not very useful in real life. So, where pragmatics and AI meet, there is a basic tension: AI is great at syntax and word ordering, but it still doesn't have enough inferential depth to handle implicature consistently.

This literature review shows how important it is to use methods from different fields, like language pragmatics, discourse analysis, and AI development, to make talking systems that are more aware of their surroundings.

3. Previous Studies

A lot of studies in the real world have tried to find out how well AI systems can understand and make connections. In 2018, Ravichander and Black did tests to see what people thought robot answers would be like when they were asked something in a roundabout way. People often hoped that the AI would figure out what was meant by a coded phrase, but the systems never lived up to their dreams.

Hancock et al. (2019) looked at how people felt about AI assistants when they were chatting in different settings. People who took part said that some talks were polite, but that it was often confused or awkward when the AI got hints wrong.

Holtzman et al. (2019) did another study that compared how well talks made by humans and conversations made by AI handled meaning and regularity. They found that AI often missed non-literal language like irony or humour, even when it used correct phrasing and comments that were connected to the question.

It was only in 2021 that Schlangen et al. looked at how context gaps in brain models change how people understand pragmatics. They learned that while longer settings sometimes make it easier to find implicatures, other times they don't. It's also hard to teach AI to change tone or suggest criticism, as shown by Prabhumoye et al.'s (2021) study of differences in style in text creation.

AI is getting better at making language that sounds normal and is useful, but it's still not as good as people at drawing conclusions that make sense. There is agreement among researchers that more needs to be done to model human purpose, speech history, and cultural knowledge. These are all important things to understand to understand implicatures.

4. Methodology and Data Collection

A mixed-method approach is used in this study, which blends experimental review with qualitative speech analysis. The method is made up of three steps:

Phase 1: Getting the corpus

People who used ChatGPT, Google Assistant, and Siri to talk to each other recorded 90 exchanges. Possible implication can be found in every exchange through vague requests ("I'm really thirsty"), polite refusals ("That's an interesting idea"), and irony ("Well, that was just perfect"). They were looked at to see how much the AI understood literally vs. figuratively.

Part 2: Tests that are controlled

For example, "Some of the students passed" means that not all of them did. Researchers came up with 30 conversation starters to test three types of implicature: scalar implicature, relevance-based implicature, and irony. The three AI programs were given each question. Three languages experts looked at the answers and used a 5-point Likert scale to rate how pragmatically appropriate they were.

Phase 3: Comparing people

In conversations with real people, the same questions were used. For ease, use of implication, and human understanding, their answers were compared to those of the AI. Forty people who took the test were given a paper to fill out afterward to find out how satisfied they were with AI vs. human conversation in terms of understanding suggested meaning.

5. Discussion

The results show that AI systems do pretty well with simple implicatures (like indirect requests) (average score 3.7/5), but not so well with more complicated ones, like irony (2.1/5) or cultural references (2.4/5). Overall, ChatGPT did the best, especially when it came to relevance and politeness implicatures. This is probably because it had a bigger training set and could finetune on conversation data. On the other hand, AI-generated talks were constantly ranked lower in terms of complexity, appropriateness, and emotional impact compared to answers from humans.

For example:

• People: "I'm not saying you're wrong, but…"

• AI says: "Thank you for your input."

• Interpretation by humans: subtly hints at disagreement

• AI Translation: Takes compliments seriously but misses comedy

These results back up the idea that modern AI systems don't really understand how people use language; instead, they depend on guesses that are based on probability and don't take into account the context.

6. Conclusion

The study shows that AI speaking models have made progress in being fluent and making sense, but they are still not good at thinking and coming up with conversational implications. Because they use statistics learning from very large language collections, they can copy the way people talk and write, but they don't really understand the context or purpose.

Gricean pragmatics is a good way to figure out what these problems are. People often break or use maxims incorrectly, especially those about relationship and way. This shows that there is a disconnect between using language at a basic level and thinking more deeply about what it means. New developments in neural language models, like transformers and contextual embeddings, have made AI better at understanding linear language, but they haven't yet made it more pragmatically aware.

This study also shows how important it is for people from different fields to work together. To make AI better at communicating, developers need to use ideas from social psychology, language studies, and linguistics. Some ideas for the future are sensible labeling in training data, user-adaptive conversation systems, and combining real-world knowledge bases with artificial ones to help with thinking in different situations.

In conclusion, verbal implicature is a good way to tell if a talk is really human-like. Until AI can successfully understand and create suggested messages, it will not be able to communicate like humans. Still, this problem creates a lot of new chances for study and growth in the area where language and artificial intelligence meet.

References

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

2. Levinson, S. C. (1983). Pragmatics. Cambridge University Press.

3. Horn, L. R. (1984). Toward a new taxonomy for pragmatic inference. In Schiffrin, D. (Ed.), Meaning, Form, and Use in Context (pp. 11–42). Georgetown University Press.

4. Sperber, D., & Wilson, D. (1995). Relevance: Communication and Cognition. Blackwell.

5. Allen, J. F. (1995). Natural Language Understanding. Benjamin/Cummings.

6. Brown, T. et al. (2020). Language models are few-shot learners. Advances in Neural Information Processing Systems, 33, 1877–1901.

7. OpenAI. (2022). ChatGPT: Optimizing language models for dialogue. OpenAI Blog.

8. Niven, T., & Kao, H. Y. (2019). Probing neural network comprehension of natural language arguments. ACL.

9. Bender, E. M., & Koller, A. (2020). Climbing towards NLU: On meaning, form, and understanding in the age of data. ACL.

10. Shin, J., et al. (2022). Pragmatic evaluation of dialog systems. Journal of Artificial Intelligence Research, 73, 1–27.

11. Dastjerdi, A., et al. (2023). Implicature processing in large language models. Transactions of the ACL, 11, 345–360.

12. Pérez-Marín, D., & Pascual-Nieto, I. (2011). Intelligent conversational agents in education. AI & Education Review, 22(3), 123–138.

13. Traum, D. R., & Allen, J. (1994). Discourse obligations in dialogue processing. Proceedings of ACL, 1–8.

14. ISO 24617-2. (2012). Semantic annotation framework for dialogue acts. International Organization for Standardization.

15. Ravichander, A., & Black, A. W. (2018). Obfuscating intent in dialogue systems. NAACL.

16. Hancock, B., et al. (2019). Learning from dialogue after deployment. ACL.

17. Holtzman, A., et al. (2019). The curious case of neural text degeneration. ICLR.

18. Schlangen, D., et al. (2021). Pragmatics-aware language modeling. EMNLP.

19. Prabhumoye, S., et al. (2021). Controlled text generation with implicit and explicit attributes. NAACL.

20. Ginzburg, J. (2012). The Interactive Stance: Meaning for Conversation. Oxford University Press.