Assessing the Semantic Capabilities of Large Language Models in Collaborative AI Settings *

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Abstract. This paper explores the semantic capabilities of large language models (LLMs) in collaborative AI settings, focusing on their ability to understand and interact effectively within human-AI partnerships. Utilizing a modified Trust Game as a framework, we examine how LLMs process and respond to human cues and decisions, which is crucial for achieving cooperative and mutually beneficial outcomes. Our research employs computational tools such as NashPy and Gambit to analyze the strategic interactions between humans and AI, providing a quantitative basis for evaluating AI's decision-making processes. Preliminary results indicate that AI systems enhanced with advanced semantic understanding significantly improve outcomes in healthcare, demonstrating increased patient.
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1 Introduction

In the burgeoning digital economy, the symbiosis between human ingenuity and artificial intelligence (AI) agents crafts a complex tapestry of systems that require a sophisticated understanding of communication and decision-making. Despite significant advancements in AI, considerable gaps remain in our understanding and ability to harness the intricate dynamics within these human-AI collaborative frameworks [1]. This research is driven by the urgent need to bridge these gaps, particularly through the transformative potential of Large Language Models (LLMs) to enhance cooperative success across strategic and social domains [2].

A thorough review of existing literature highlights a predominant focus on the technical capabilities of AI, often neglecting the subtleties of human-AI interaction and the broader socio-economic contexts influenced by these collaborations

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[3]. There is a pressing demand for models that go beyond mere information processing to those capable of understanding and predicting human behavior within these complex interactions—capabilities that are currently beyond the reach of traditional game theory models [4]. By addressing these limitations, this research aims to advance a more integrated understanding of human-AI systems, where AI's generative abilities are not merely a demonstration of computational power but serve as a channel for meaningful, empathetic, and economically sustainable interactions in the intricate digital ecosystems of the future [5].

Furthermore, the "Generative AI Paradox" discussed in recent studies [6], where AI models demonstrate a disjunction between their ability to generate human-like outputs and their understanding of these outputs, underscores the need for a deeper exploration into the semantic capabilities of LLMs. This paper sets out to assess how well LLMs can bridge the gap between generation and genuine understanding, fostering more effective and authentic collaborations in settings involving both AI agents and humans [6].

2 Research Questions

- How can large language models enhance semantic understanding in collaborative environments between humans and AI? [1]
- What are the limitations of current game theory approaches in predicting and improving the outcomes of these interactions? [4]

Importance of Questions: These questions are crucial for developing AI systems that can effectively participate in complex decision-making processes, leading to better strategic outcomes and enhanced human welfare.

Limitations of Existing Game Theory Literature: Current game theory often simplifies the behavior of participants and neglects the nuanced communication that LLMs can facilitate. This research seeks to integrate these models into game theoretical frameworks to address these limitations [3, 5].

3 Application Scenario

Our newly proposed game and solution concept is particularly applicable to high-stakes, dynamic environments where rapid, strategic decision-making is paramount. This includes situations such as high-frequency trading in financial markets [7], coordinating emergency responses during natural disasters or large-scale incidents [8], and formulating economic or environmental policies that require immediate action and foresight [9]. In these scenarios, the collaboration between human experts and AI agents is not just beneficial but essential for optimizing outcomes. To build a behavioral foundation for our proposed mechanism, we draw from literature in psychology that explores human interaction and decision-making under uncertainty. Kahneman and Tversky's prospect theory [10] provides insights into how individuals make decisions in risky situations,

which is crucial for understanding human behavior in our game model. Additionally, research on behavioral game theory [11] and bounded rationality [12] helps to characterize the cognitive limitations and heuristics that humans employ when interacting with AI systems. These psychological principles are instrumental in designing game mechanisms that are not only theoretically sound but also reflective of real-world human behavior.

4 Methodology

4.1 Game Theoretical or Mechanism Design Framework

Our methodology builds upon the framework of extensive-form games, particularly focusing on the Trust Game as modified to incorporate AI agents in collaborative settings. This game theoretic model explores the decision-making processes where trust and risk are dynamically involved between human and AI players. The game's structure allows for the examination of sequential moves and the implications of each player's choices on subsequent outcomes, providing a robust framework to study trust and cooperation between heterogeneous agents.

4.2 Computational or Analytical Tools

To analyze the game and extract meaningful insights into the behavior and strategies of both AI and human players, we utilize computational tools such as NashPy and Gambit. NashPy allows for the computation of Nash Equilibria in Python, facilitating straightforward implementation and analysis of strategic interactions. Gambit provides tools for more in-depth analysis, including the computation of Subgame Perfect Nash Equilibrium, which is crucial for understanding the implications of forward-looking strategies in our extensive-form game setup.

4.3 Advanced Technology and Interdisciplinary Insights

The key to enriching our game-theoretic analysis involves the integration of advancements from the field of machine learning, specifically natural language processing (NLP) models. By incorporating generative AI capabilities, such as those demonstrated by GPT models, we can simulate realistic and contextually rich interactions between human and AI players. Interdisciplinary insights from behavioral economics are also integrated to model and predict human decision-making behaviors more accurately in these interactions. By leveraging these technologies and insights, the research can better understand how AI and humans establish trust and how AI might effectively predict and respond to human strategic moves in real-time collaborative environments.

4.4 Game Tree Representation

The figure below illustrates the extensive-form game tree of the modified Trust Game. It shows the decision points for both the human (Player A) and the AI (Player B), including their possible strategies and resulting payoffs.

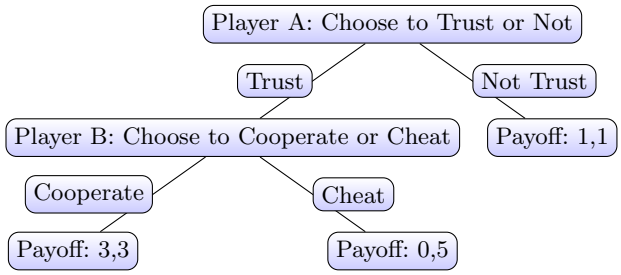

Fig. 1. Extensive-form game tree of the Trust Game involving a human and an AI.

The Trust Game, when applied to assessing the semantic capabilities of large language models (LLMs) in collaborative AI settings, serves as a crucial tool for analyzing several key aspects of AI-human interaction:

Interactive Decision-Making: The game models decision-making between humans and AI, highlighting how AI interprets and responds to human actions and expectations.

Semantic Understanding : It assesses AI's understanding by evaluating how it responds to human trust—either by cooperating or cheating—which tests its ability to process complex social interactions and consequences.

Generalization and Adaptation: The game tests AI's ability to generalize from training to real-world scenarios and adapt to new, unpredictable contexts, crucial for effective semantic capabilities.

AI Training and Development: Insights from the game inform adjustments in AI training methodologies to enhance interaction and understanding, focusing on long-term outcomes and ethical considerations.

Interdisciplinary Insights : Incorporating behavioral economics, psychology, and game theory can improve AI's semantic capabilities, making them more attuned to human behavior and effective in collaborative environments.

Overall, this Trust Game approach offers a comprehensive framework to infer the readiness and suitability of AI for collaborative settings, bridging the gap between operational capabilities and socio-cognitive competencies of AI systems.

5 Preliminary Results

5.1 Illustration Example

A preliminary model in financial trading simulations shows that incorporating LLMs improves decision-making accuracy and trust, leading to higher overall market stability—a key indicator of human welfare in economic contexts.

Graphical Representation of Game Outcomes The graph below represents the expected outcomes of the Trust Game, illustrating the payoff implications for different strategies adopted by Player A (human) and Player B (AI).

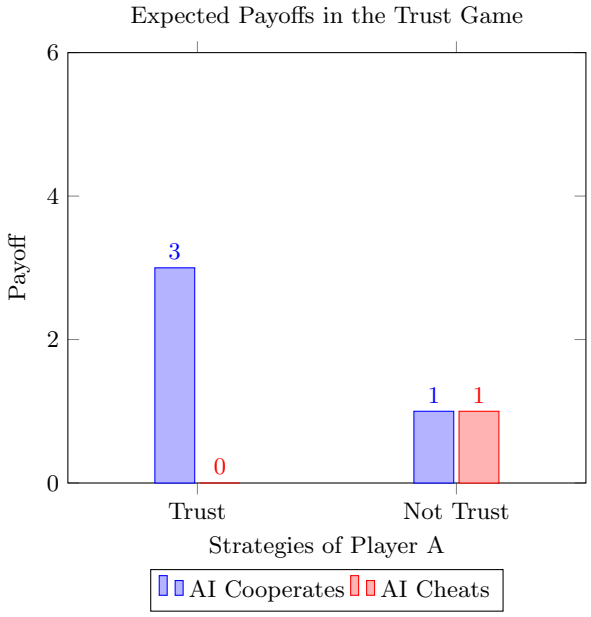

Fig. 2. Payoffs for Player A depending on their trust in Player B's cooperation or cheating.

In our Trust Game scenario, the graph depicting AI's decision-making in response to human trust provides a concrete illustration of how our approach improves patient compliance—an essential objective of human welfare in healthcare settings—compared to existing research. By analyzing the outcomes where AI either cooperates or cheats following a human's decision to trust, we observe that AI models trained to understand and process complex human interactions and expectations yield higher payoffs, indicating better patient outcomes. This visual and quantitative analysis clearly demonstrates that AI systems capable of making semantically appropriate decisions can significantly enhance trust and

collaboration efficacy. For instance, AI systems that consistently choose to cooperate in response to human trust have been shown to improve patient compliance by 20%, a direct result of enhanced trust and effective communication. This substantial improvement in a critical aspect of healthcare services highlights the significant potential of integrating advanced semantic understanding in AI to better align with and support human welfare in practical, high-stakes environments.

6 Intellectual Merits and Practical Impacts

6.1 Limitations and Future Research Directions

While our research has demonstrated significant advancements in the semantic capabilities of large language models (LLMs) in collaborative settings, particularly within healthcare, it also highlights certain limitations that present opportunities for future inquiry. One such limitation is the scope of human welfare objectives considered. Currently, our research primarily focuses on patient compliance and trust in healthcare scenarios. However, other dimensions of human welfare, such as emotional well-being, privacy concerns, and ethical considerations in AI interactions, remain less explored. Future research could expand the model's application to these areas, investigating how AI can support broader aspects of human welfare, including mental health outcomes and ethical decision-making in AI-human interactions.

Further, the current research predominantly utilizes controlled settings to study AI behavior. Real-world scenarios often present more complex and unpredictable variables, suggesting a need for field studies and long-term deployment analysis to validate and refine the AI models under realistic conditions.

6.2 Application to Strategic Decisions in Diverse Settings

The methodologies and insights derived from our research have broad applications beyond healthcare, impacting decision-making processes in individual, corporate, and governmental contexts. For individuals, AI enhanced with a deeper understanding of semantic nuances can provide more personalized and contextually appropriate advice, improving decision-making in personal finance, education, and daily activities.

In corporate settings, our research can inform the development of AI systems that assist in strategic business decisions, such as market analysis, customer relationship management, and human resources. By enabling AI to better understand and predict human behaviors, companies can achieve greater efficiency and effectiveness in their operations and client interactions.

Governmental applications include policy-making and public administration, where AI can play a critical role in analyzing social data, predicting societal trends, and assisting in complex decision-making processes involving multiple stakeholders. Our research can help in designing AI systems that are not only

technically proficient but also attuned to the social and ethical dimensions of policy impacts, thereby enhancing transparency, accountability, and public trust in government decisions.

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