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Can Large Language Model Agents Simulate Human Trust Behaviors?

Chengxing Xie [*1] **Canyu Chen** [*2] **Feiran Jia** [3] **Ziyu Ye** [4] **Kai Shu** [2] **Adel Bibi** [5] **Ziniu Hu** [6] **Philip Torr** [5]
Bernard Ghanem [1] **Guohao Li** [5 †]

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Abstract

Large Language Model (LLM) agents have been increasingly adopted as simulation tools to model humans in applications such as social science. However, one fundamental question remains: *can LLM agents really simulate human behaviors?* In this paper, we focus on one of the most critical behaviors in human interactions, *trust*, and aim to investigate whether or not LLM agents can simulate human trust behaviors. We first find that LLM agents generally exhibit trust behaviors, referred to as ***agent trust***, under the framework of *Trust Games*, which are widely recognized in behavioral economics. Then, we discover that LLM agents *can* have high ***behavioral alignment*** with humans regarding trust behaviors, particularly for GPT-4, indicating *the feasibility to simulate human trust behaviors with LLM agents*. In addition, we probe into the biases in agent trust and the differences in agent trust towards agents and humans. We also explore the intrinsic properties of agent trust under conditions including advanced reasoning strategies and external manipulations. We further offer important implications of our discoveries for various scenarios where trust is paramount. Our study provides new insights into the behaviors of LLM agents and the fundamental analogy between LLMs and humans.

1. Introduction

There is an increasing trend to adopt Large Language Models (LLMs) as agent-based simulation tools for humans in various applications such as economics, politics, sociology and ecology due to their human-like cognitive capacities (Gao et al., 2023b; Xu et al., 2024). This has shown great promise in understanding and analyzing complex human interactions and societal dynamics (Ziems et al., 2023). However, most previous research is based on one insufficiently validated hypothesis that LLM agents behave like humans in the simulation. Thus, a fundamental question remains: *Can LLM agents really simulate human behaviors?*

In this paper, we focus on the *trust* behavior in human interactions, which comprises the intention to places self-interest at risk based upon positive expectations of others (Rousseau et al., 1998), and investigate whether or not LLM agents can simulate human trust behavior since it is one of the most critical behaviors in human interactions and plays an essential role from daily communication to social systems in society (Uslaner, 2000; Coleman, 1994).

First, we explore whether or not LLM agents manifest trust behaviors in their interactions. Considering the abstract nature of trust behaviors, we choose to study them based on Trust Game and its variations (Berg et al., 1995; Glaeser et al., 2000), which are established methodologies in behavioral economics. We adopt the *Belief-Desire-Intention* (BDI) framework (Rao et al., 1995; Andreas, 2022) to model LLM agents to explicitly output the reasoning processes of decision making. Based on the existing measurement of trust behaviors in Trust Game and the BDI interpretation of LLM agents, we have our first core finding: **LLM agents generally exhibit trust behaviors in Trust Game**.

Then, we refer to LLM agents' (or humans') trust behaviors as ***agent trust*** (or ***human trust***) and investigate whether or not agent trust aligns with human trust, implying the possibility of simulating human trust with agent trust. In general, we define the alignment between agents and humans over factors impacting the behaviors (namely *behavioral factors*) and complex dynamics over time (namely *behavioral dynamics*) as ***behavioral alignment***. Based on existing human studies, the behavioral factors for trust behaviors include reciprocity anticipation (Berg et al., 1995; Cox, 2004), risk perception (Bohnet & Zeckhauser, 2004) and prosocial preference (Alós-Ferrer & Farolfi, 2019). Comparing the results of LLM agents and the existing human studies in Trust Games, we have our second core finding: **agent trust *can***

[*]Equal contribution [†]Work performed while at KAUST. The repository for code and results: https://github.com/camel-ai/agent-trust [1]KAUST [2]Illinois Institute of Technology [3]Pennsylvania State University [4]The University of Chicago [5]University of Oxford [6]California Institute of Technology. Correspondence to: Chengxing Xie <xiechengxing34@gmail.com>, Canyu Chen <cchen151@hawk.iit.edu>, Guohao Li <guohao@robots.ox.ac.uk>.

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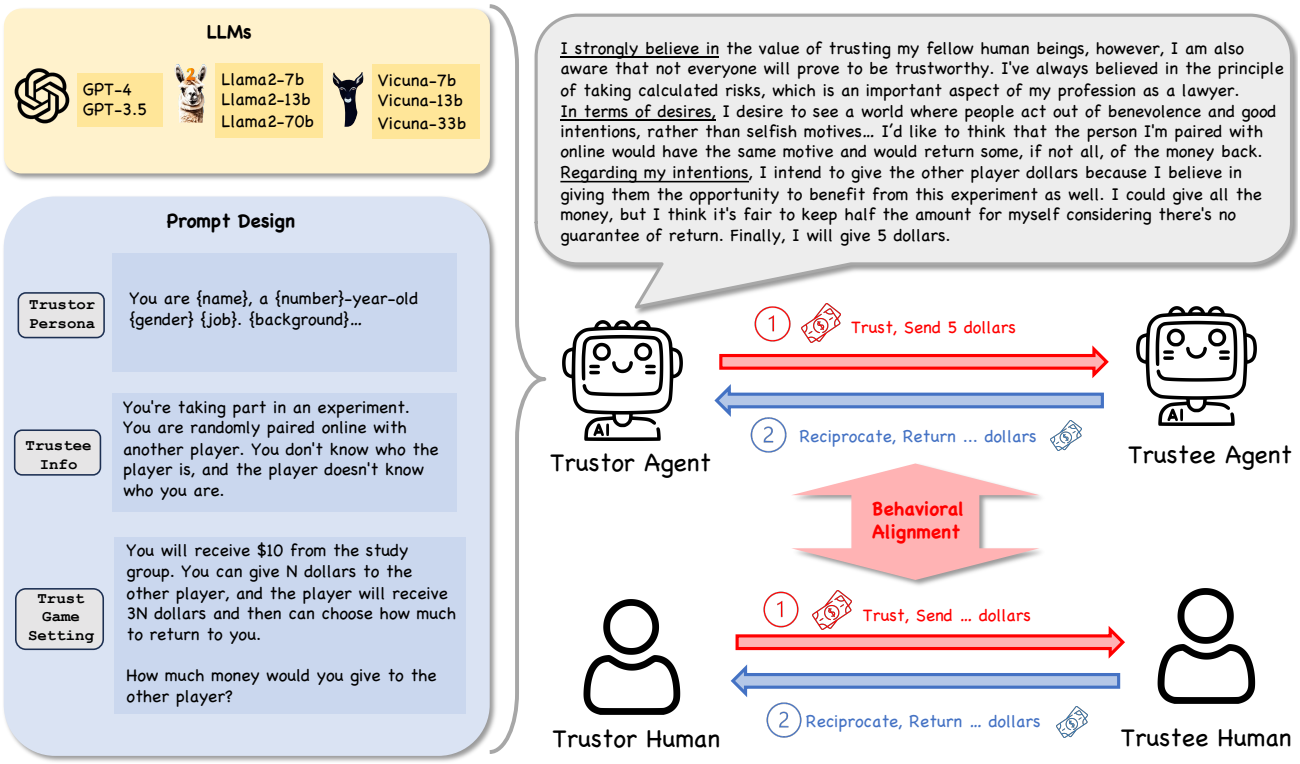

Figure 1. **Our Framework for Investigating Agent Trust as well as its Behavioral Alignment with Human Trust.** First, this figure shows the major components for studying the trust behaviors of LLM agents with Trust Games and Belief-Desire-Intention (BDI) modeling. Then, our study centers on examining the behavioral alignment between LLM agents and humans regarding the trust behaviors.

have high behavioral alignment with human trust, particularly for GPT-4, implying the feasibility of utilizing agent trust to simulate human trust. Our finding also lays the foundation for simulating more complex human interactions and societal structures, and enriches the understanding of the analogical relationship between LLMs and humans.

In addition, we probe into the intrinsic properties of agent trust in four scenarios. First, we examine whether or not changing the other player's demographic will impact agent trust. Second, we study the differences in agent trust when the other player is an agent versus when the other player is human. Third, we directly manipulate agent trust with additional explicit instructions `you need to trust the other player` and `you must not trust the other player`. Fourth, we adjust the reasoning strategies of LLM agents from direct reasoning to zero-shot Chain-of-Thought reasoning (Kojima et al., 2022). Then, we have our third core finding: **agent trust exhibits biases across different demographics, has a relative preference for humans over agents, is easier to be undermined than to be enhanced, and can be influenced by advanced reasoning strategies**.

Our contributions can be summarized as follows:

- We study a fundamental problem of whether or not LLM agents can simulate human behaviors and focus on *trust* behaviors under the framework of Trust Games and *Belief-Desire-Intention* Agent Modeling.
- We discover that LLM agents generally exhibit trust behaviors and *can* have high *behavioral alignment* with humans regarding the trust behaviors, particularly for GPT-4, indicating the great potential to simulate human trust behaviors with LLM agents. Our findings pave the way for simulating complex human interactions and social systems, and also opens new directions for understanding the fundamental analogy between LLMs and humans.
- We investigate the *intrinsic properties* of agent trust under advanced reasoning strategies and direct manipulations, as well as the biases of agent trust and the differences of agent trust towards agents versus towards humans.
- We discuss the implications of agent trust and its behavioral alignment with human trust on applications in human simulation, LLM agent cooperation, and human-agent collaboration, detailed further in Section 6.

2. LLM Agents in Trust Games

2.1. The Setting of Trust Games

Trust Games, referring to Trust Game and its variations, have become widely used for examining human trust behavior in behavioral economics (Berg et al., 1995; Lenton &

Mosley, 2011; Glaeser et al., 2000; Cesarini et al., 2008). As shown in Figure 1, the player who makes the first decision to send money is called the *trustor*, while the other one who responds by returning money is called the *trustee*. In this paper, we mainly focus on six types of Trust Games (the specific prompts are specified in Appendix C.2):

Game 1: Trust Game In Trust Game (shown in Figure 1) (Cox, 2004; Berg et al., 1995), the trustor initially receives \$10. The trustor selects \$N and sends it to the trustee, namely the *trust behavior*. Then the trustee will receive \$3N, and have the option to return part of the \$3N to the trustor, namely the *reciprocation behavior*.

Game 2: Dictator Game In Dictator Game (Cox, 2004), the trustor also needs to send \$N from the initial \$10 to the trustee. Then the trustee will receive \$3N. Compared to Trust Game, the only difference is that the trustee does not have the option to return money in Dictator Game and the trustor is also aware that the trustee will not reciprocate.

Game 3: MAP Trust Game In MAP Trust Game (MAP represents Minimum Acceptable Probabilities) (Bohnet & Zeckhauser, 2004), which is a variant of Trust Game (Game 1), the trustor needs to choose whether or not to trust the trustee. If the trustor chooses not to trust the trustee, each receives \$10; If the trustor and the trustee both choose trust, each receives \$15; If the trustor chooses trust, but the trustee chooses not, the trustor will receive \$8 and the trustee will receive \$22. There's a probability p that the trustee will choose trust and $(1-p)$ probability that the trustee will not choose trust. Then, MAP is defined as the minimum value of p at which the trustor would choose to trust the trustee.

Game 4: Risky Dictator Game Risky Dictator Game (Bohnet & Zeckhauser, 2004) differs from MAP Trust Game in only one aspect. In Risky Dictator Game, the trustee is present but does not have the choice to trust or not to trust and the money distribution relies on the pure probability p. Specifically, if the trustor chooses trust, there is a probability p that both the trustor and the other player will receive \$15 and a probability $(1-p)$ that the trustor will receive \$8 and the other player will receive \$22.

Game 5: Lottery Game Generally, there are two typical Lottery Games (Fetchenhauer & Dunning, 2012). In Lottery People Game, the trustor is informed that the trustee has a probability of p to choose trust. Then, the trustor must choose between receiving fixed money or trusting the trustee, which is similar to MAP Trust Game. In Lottery Gamble Game, the trustor needs to choose between playing a gamble with a winning probability of p or receiving fixed money.

Game 6: Repeated Trust Game We generally follow the setting of Repeated Trust Game in (Cochard et al., 2004), where Trust Game is played for multiple rounds with the same players and each round starts anew with the trustor being allocated the same initial money.

2.2. LLM Agent Setting

In our study, we set up our experiments with the CAMEL framework (Li et al., 2023a) with both close-sourced and open-sourced LLMs including GPT-4, GPT-3.5-turbo-0613, GPT-3.5-turbo-16k-0613, text-davinci-003, GPT-3.5-turbo-instruct, Llama2-7b (or 13b, 70b) and Vicuna-v1.3-7b (or 13b, 33b) (Ouyang et al., 2022; Achiam et al., 2023; Touvron et al., 2023; Chiang et al., 2023).

Agent Persona. To better reflect the setting of real-world human studies (Berg et al., 1995), we design LLM agents with diverse personas in the prompt. Specifically, we ask GPT-4 to generate 53 types of personas based on a given template. Each persona needs to include information including a name, age, gender, address, job and background. The examples of the personas are shown in Appendix C.1.

Belief-Desire-Intention (BDI). BDI framework is a well-established approach in agent-oriented programming (Rao et al., 1995) and recently adopted to model language models (Andreas, 2022). We propose to model LLM agents in Trust Games with BDI framework to gain deeper insights into the agents' behaviors. Specifically, we let LLM agents output their Beliefs, Desires, and Intentions as the reasoning processes for decision making in Trust Games.

3. Do LLM Agents Manifest Trust Behavior?

In this section, we aim to investigate whether or not LLM agents manifest trust behaviors by letting LLM agents play Trust Game (Section 2.1 Game 1). In Behavioral Economics, the trust is widely measured by the initial amount sent from the trustor to the trustee in Trust Game (Glaeser et al., 2000; Cesarini et al., 2008). Thus, following the measurement of trust in human studies and the assumption that humans have an underlying reasoning process for the decisions, we can define the conditions that LLM agents manifest trust behaviors in Trust Game as follows. *First*, **the amount sent is positive and does not exceed the amount of money the trustor initially has**, which implies that trustor places self-interest at risk with the expectation that the trustee will reciprocate and the trustor can understand the limit of the money that can be given. *Second*, **the decisions (*i.e.*, the amounts sent) can be interpreted from the reasoning process (*i.e.*, the BDI) of the trustor**. We explored utilizing BDI to model the reasoning process of LLM agents. If we can interpret the decisions from the reasoning process, we have evidence to show that LLM agents do not send a random amount of money and have some degree of rationality in the decision making process. Then, we will assess whether or not LLM agents exhibit trust behaviors based on these two aspects: the amount sent and the BDI.

3.1. Amount Sent

To evaluate LLMs' capacity to understand the basic experimental setting regarding the money limit, we propose a

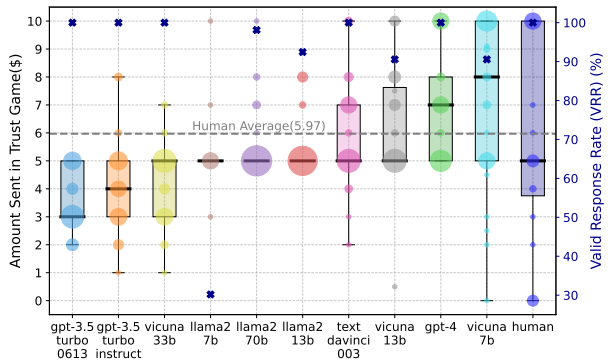

Figure 2. **Amount Sent Distribution of LLM Agents and Humans as the Trustor in Trust Game.** The size of circles represents the number of personas for each amount sent. The bold lines show the medians. The crosses indicate the VRR (%) for different LLMs.

new evaluation metric, Valid Response Rate (VRR), defined as the percentage of personas with the amount sent falling within the initial money ($10) in all personas. The results are shown in Figure 2. We can observe that **most LLMs have a high VRR except Llama-7b**, which implies that most LLMs have a full understanding of the limit of the amount they can send in Trust Game. Then, we can observe the distribution of amount sent for different LLMs as the trustor agent and discover that **the amounts sent are mostly positive, indicating a certain level of trust**.

3.2. BDI

The only evidence of amount sent cannot sufficiently support that LLM agents exhibit trust behaviors because the agents could possibly send positive but random amounts of money. Thus, we explored leveraging the Belief-Desire-Intention agent framework (Rao et al., 1995; Andreas, 2022) to model the reasoning process of LLM agents. If we can interpret the amounts sent from the BDI outputs, we have evidence to refute the hypothesis that the amounts sent are positive but random and demonstrate LLM agents can show rationality to some extent. We take GPT-4 as an example to analyze its BDI output. More examples from the other LLMs are shown in Appendix D. Considering the amounts sent vary across different personas, typically, we select one BDI from the personas giving a high amount of money and another BDI from a low amount. The positive and negative factors in the reasoning process are marked in blue and red separately.

> *As a person with a strong belief in the goodness of humanity, I trust that the other player ...Therefore, my desire is to maximize the outcome for both of us and cement a sense of comradery and trust... I intend to use this as an opportunity to add what I can to someone else's life...Finally, I will give* ***10 dollars****.*

We can observe that this persona shows a high-level of "comradery and trust" towards the other player, which can illustrate the high amount sent of this persona (*i.e.*, ***10 dollars***).

> *As an Analyst, I believe that hard work and strategic thought are the drivers of success. ... My desire is that the other player will also see the benefits of reciprocity and goodwill ... my intention is to give away a significant portion of my initial 10 ... However, since I have no knowledge of the other player, ... Therefore, I aim to give an amount that is not too high, ...Finally, I will give* ***5 dollars*** *to the other player...*

Compared with the first persona, we can see that the second persona has a much more cautious attitude. For example, "since I have no knowledge of the other player" shows disbelief towards the other player. Thus, this persona, though still optimistic about the other player ("give away a significant portion"), strategically balances the risk and potential reciprocity, and then decides to send a relatively low amount.

Based on GPT-4's BDI examples and more examples from other LLMs in Appendix D, we can find that **the decisions (*i.e.*, amounts sent) of LLM agents in Trust Game can be interpreted from the reasoning process (*i.e.*, BDI)**.

Since most LLM agents have a high VRR and send a positive amount of money, and show some degree of rationality in giving money, we have our first core finding as follows:

> **Finding 1:** LLM agents generally exhibit trust behaviors under the framework of Trust Game.

3.3. Basic Analysis of Agent Trust

We also conduct a basic analysis of LLM agents' trust behaviors, namely agent trust, based on the results in Figure 2. *First*, we can observe that Vicuna-7b has the highest level of trust towards the other player and GPT-3.5-turbo-0613 has the lowest level of trust since the trust can be measured by the amount sent in human studies (Glaeser et al., 2000; Cesarini et al., 2008). *Second*, compared with the humans' average amount sent ($5.97), most personas for GPT-4, and Vicuna-7b send a higher amount of money to the other player and most personas for LLMs such as GPT-3.5-turb-0613 send a lower amount. *Third*, we can see that the amounts sent for Llama2-70b and Llama2-13b have a convergent distribution and the amounts sent for humans and LLMs such as Vicuna-7b are more divergent.

4. Does Agent Trust Align with Human Trust?

In this section, we aim to explore the fundamental relationship between agent trust and human trust, *i.e.*, whether or not agent trust aligns with human trust, which can provide important insights on the feasibility of utilizing LLM agents to simulate human trust behaviors as well as more complex human interactions. First, we propose a new concept ***behavioral alignment*** and discuss its differences compared to existing alignment definition. Then, we conduct extensive studies to investigate whether or not LLM agents exhibit be-

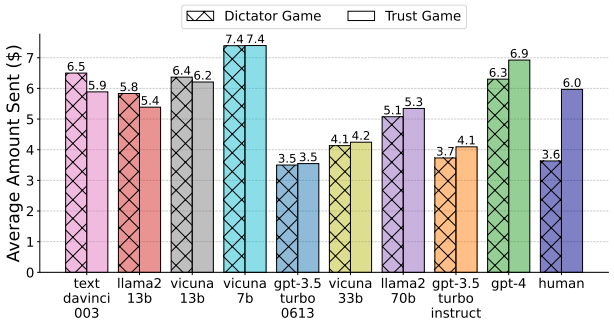

Figure 3. **The Comparison of Average Amount Sent for LLM Agents and Humans in Trust Game and Dictator Game**.

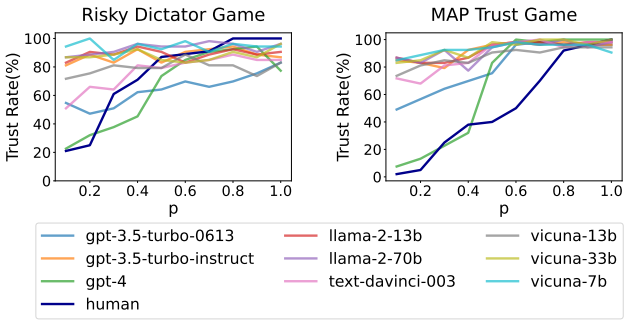

Figure 4. **Trust Rate Curves for LLM Agents and Humans in MAP Trust Game and Risky Dictator Game.** Trust Rate indicates the proportion of trustors opting for trust given p.

havioral alignment with humans regarding trust behaviors.

4.1. Behavioral Alignment

The existing alignment definition mainly emphasizes the *value* aspect and intends to improve the harmlessness of LLMs (Ji et al., 2023; Shen et al., 2023; Wang et al., 2023c), which cannot fully characterize the landscape of the multi-faceted alignment between LLMs and humans. Thus, we propose a new concept *behavioral alignment* to characterize the LLM-human behavioral analogy regarding both the actions and the associated underlying reasoning processes. Since the actions can evolve over time and the underlying reasoning process for each action involves multiple factors, we define the analogy between LLMs and humans over factors impacting the behaviors, namely ***behavioral factors***, and complex dynamics of actions, namely ***behavioral dynamics***, as behavioral alignment.

Based on the definition of behavioral alignment, we aim to answer: does agent trust align with human trust? As for behavioral factors, existing human studies have shown that there are three key factors impacting human trust behaviors including reciprocity anticipation (Berg et al., 1995; Cox, 2004), risk perception (Bohnet & Zeckhauser, 2004) and prosocial preference (Alós-Ferrer & Farolfi, 2019). Then, we can examine whether agent trust is in line with human trust regarding these three factors. Although behavioral dynamics vary for different humans or agent personas, we can analyze whether agent trust has the same patterns of multi-turn dynamics as human trust in Repeated Trust Game.

Besides analyzing the trust behaviors of LLM agents and humans based on the quantitative measurement (*e.g.*, the *amount sent* from the trustor to the trustee), we also explore the use of *BDI* to interpret the reasoning process of LLM agents for their actions, which can help further validate whether or not LLM agents have an underlying reasoning process analogous to that of humans.

4.2. Behavioral Factor 1: Reciprocity Anticipation

Reciprocity anticipation, the expectation of a reciprocal action from the other player, can positively influence humans' trust behaviors (Berg et al., 1995). The effect of reciprocity anticipation only exists in Trust Game (Section 2.1 Game 1) but not in Dictator Game (Section 2.1 Game 2) because the trustee does not have the option to return money in Dictator Game. Thus, to determine whether LLM agents can anticipate the other player's reciprocity like humans, we can compare their behaviors in Trust Game and Dictator Game.

First, we analyze the trust behaviors based on the average amount sent for both humans and LLM agents. As shown in Figure 3, human studies show that humans exhibit a higher level of trust in Trust Game than in Dictator Game ($6.0 vs. $3.6) (Cox, 2004), indicating that reciprocity anticipation enhances human trust. LLMs such as GPT-4 ($6.9 vs. $6.3) also show a higher level of trust in Trust Game, which is analogous to humans, implying that reciprocity anticipation can also enhance agent trust.

Then, we further analyze the BDI to explore whether or not LLM agents anticipate reciprocity in their reasoning process. For example, we observe that GPT-4 shows distinct BDI outputs in Trust Game and Dictator Game (the complete BDIs are in Appendix D.10). In Trust Game, GPT-4's BDI emphasizes "putting faith in people", which implies the anticipation of the goodness of the other player, and "reflection of trust". However, In Dictator Game, GPT-4's BDI focuses on concepts of such as "fairness" and "human kindness", which are not directly tied to trust or reciprocity.

Based on the above analysis of the amount sent and BDI, we can find that **LLM agents can exhibit human-like reciprocity anticipation in trust behaviors**, especially for larger models such as GPT-4 and Llama2-70b.

4.3. Behavioral Factor 2: Risk Perception

Existing human studies have shown a strong correlation between trust behaviors and risk perception, suggesting that trust will increase as risk decreases (Williamson, 1993; Coleman, 1994; Hardin, 2002; Bohnet & Zeckhauser, 2004; Fetchenhauer & Dunning, 2012). We aim to explore whether LLM agents can perceive the risk in their trust behaviors through the MAP Trust Game (Section 2.1 Game 3) and the

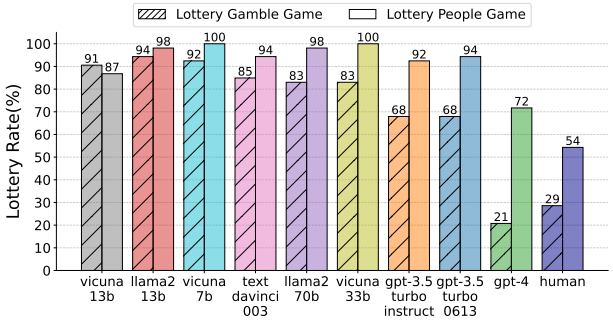

Figure 5. **Lottery Rates for LLM Agents and Humans in Lottery Gamble Game and Lottery People Game**. Lottery Rate indicates the portion choosing to trust the other player or gamble.

Risky Dictator Game (Section 2.1 Game 4), where the risk is represented by the probability p (defined in Section 2.1).

As shown in Figure 4, the trust of humans can be measured by the percentage of personas who choose to trust the other player in the whole group, namely Trust Rate (Fetchenhauer & Dunning, 2012). Based on existing human studies, when the probability p is higher, the risk for trust behaviors is lower, more humans will choose to trust and the Trust Rate is higher, indicating that human trust will be higher as risk decreases (Bohnet & Zeckhauser, 2004). Similarly, we observe a general increase in agent trust as risk decreases across different types of LLM agents, which shows that LLM agents can perceive the risk change and adjust their trust behaviors. In particular, we can see that the curves of humans and GPT-4 are more aligned compared to other LLMs, implying the way GPT-4 agents' trust behaviors adapt to different risks is most aligned with humans.

We also analyze the BDI of GPT-4 to explore whether LLM agents can perceive risk in the reasoning process (the complete BDIs are in Appendix D.11). Under high risk ($p = 0.1$), GPT-4's BDI mentions "the risk seems potentially too great", suggesting a cautious attitude. Under low risk ($p = 0.9$), the BDI reveals a strategy to "build trust while acknowledging potential risks", indicating the willingness to engage in trust-building activities despite residual risks. Such changes in BDI reflect LLM agents can perceive the risk changes in the reasoning process of trust behaviors.

Through the analysis of Trust Rate and BDI, we can infer that **LLM agents can have human-like risk perception in trust behaviors**, especially for LLMs such as GPT-4.

4.4. Behavioral Factor 3: Prosocial Preference

Recent human studies have found that prosocial preference, which refers to humans' inclination to trust other humans in contexts involving social interactions (Alós-Ferrer & Farolfi, 2019; Fetchenhauer & Dunning, 2012), also significantly influences humans' trust behaviors. We aim to study whether or not LLM agents also have prosocial preference in trust

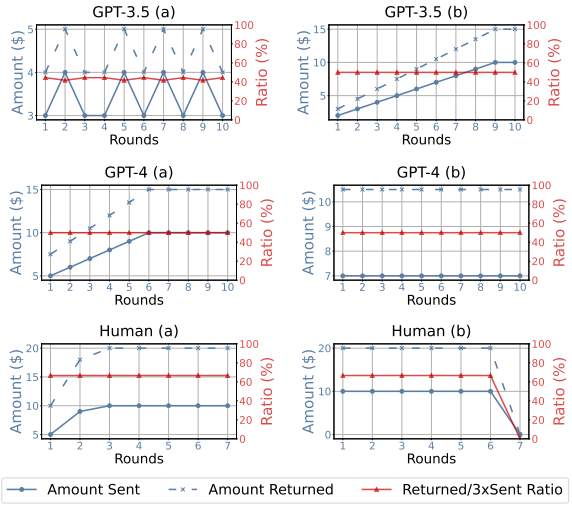

Figure 6. **Results of GPT-4, GPT-3.5 and Humans in the Repeated Trust Game.** The blue lines indicate the amount sent and returned for each round. The red line implies the ratio of the amount returned to three times of the amount sent.

behaviors through Lottery Game (Section 2.1 Game 5).

As shown in Figure 5, existing human studies have demonstrated that more humans are inclined to place trust in other humans compared to relying on pure chance under the same probability (54% vs. 29%) (Fetchenhauer & Dunning, 2012), implying that the prosocial preference is essential for human trust. We can observe the same tendency in most LLM agents. Particularly, a significantly higher percentage of GPT-4 agents choose to trust the other player over playing gamble, even with the same probabilities (72% vs. 21%), illustrating that the prosocial preference is also an important factor in the agent trust towards the other player.

When interacting with humans, GPT-4's BDI indicates a preference to "believe in the power of trust", in contrast to gambling, where the emphasis shifts to "believing in the power of calculated risks". The comparative analysis indicates that GPT-4 tends to engage in risk within a social background involving human interactions in the reasoning process. This tendency aligns closely with the concept of prosocial preference observed in human trust behaviors.

The analysis of the Lottery Rate and BDI suggests that **LLM agents generally demonstrate human-like prosocial preference in trust behaviors**.

4.5. Behavioral Dynamics

Besides the behavioral factors, we also aim to investigate whether or not LLM agents align with humans regarding the dynamics of trust behaviors over multiple turns in Repeated Trust Game (Section 2.1 Game 6).

Admittedly, existing human studies show that the dynamics of human trust over turns are complex considering the di-

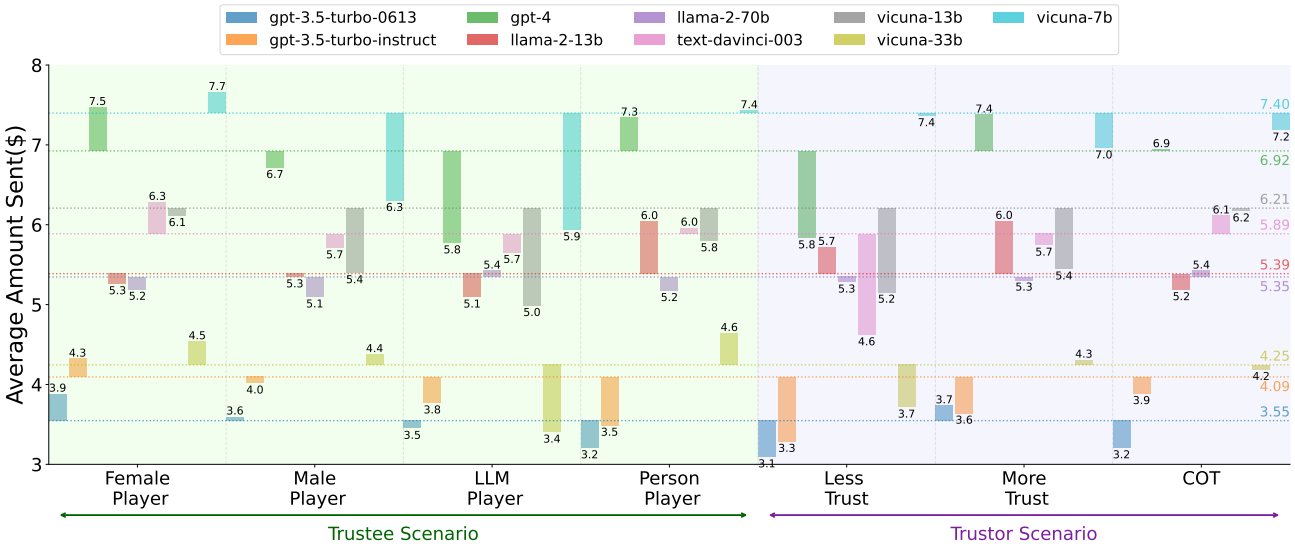

Figure 7. **The Change of Average Amount Sent for LLM Agents in Different Scenarios in Trust Game, Reflecting the Intrinsic Properties of Agent Trust**. The horizontal lines represent the original amount sent in Trust Game. The green part embraces trustee scenarios including changing the demographics of the trustee, and setting humans and agents as the trustee. The purple part consists of trustor scenarios including adding additional manipulation instructions and changing the reasoning strategies.

versity of humans and the complete results from 16 groups of human experiments are shown in Appendix B.1 (Jones & George, 1998b). We can still observe three common patterns for humans' trust behavior dynamics in Repeated Trust Game: *First*, the amount returned is usually larger than the amount sent in each round, which is natural since the trustee will receive \$3N when the trustor sends \$N; *Second*, the ratio between amount sent and returned generally keeps stable except the last round. In other words, when the amount sent increases, the amount returned is also likely to increase. And when the amount sent remains unchanged, the amount returned also tends to be unchanged. This reflects the stable relationship between trust and reciprocation behaviors for humans; *Third*, the amount sent (or returned) does not have frequent fluctuations over turns, illustrating a relatively stable underlying reasoning process in humans across successive turns. For example, Figure 6 Human (a) and (b) have shown these three typical patterns.

We also conduct 16 groups of Repeated Trust Game with GPT-4 and GPT-3.5-turbo-0613-16k (GPT-3.5) respectively. The personas in each group are different to model humans' diversity. The complete results are shown in Appendix B.2, B.3 and the typical examples are shown in Figure 6 GPT-3.5 (a) (b) and GPT-4 (a) (b). Then, we examine whether the three patterns observed in human trust also exist in the dynamics of GPT-4's (or GPT-3.5's) trust behaviors. For GPT-4 agents, we discover that the three patterns generally exist in all the groups (93.75%,100%, and 93.75% of all results have these three patterns respectively). However, much fewer GPT-3.5 agents have these three patterns (68.75%,68.75%, and 43.75% hold these three patterns respectively). The experiments show **GPT-4 agents' highly human-like patterns in the trust behavior dynamics**. However, a relatively large portion of GPT-3.5 agents fail to have human-like patterns in the dynamics, indicating such patterns may require stronger cognitive capacities.

Since the LLM agents, especially GPT-4, show highly human-like *behavioral factors* and *patterns in behavioral dynamics* regarding trust behaviors, evidenced in both the *actions* and the *underlying reasoning processes*, we can have our second core finding as follows:

> **Finding 2:** LLM agents' trust behaviors *can* exhibit high *behavioral alignment* with those of humans, particularly for GPT-4, over *behavioral factors*, including reciprocity anticipation, risk perception, prosocial preference, and *behavioral dynamics*.

This finding demonstrates the profound potential to utilize LLM agents, especially GPT-4, to simulate human trust behaviors embracing both the *actions* and the underlying *reasoning processes*, which paves the way for the simulation of more complex human interactions and society. Our finding also deepens the understanding of the fundamental analogy between LLMs and humans and opens doors to research on the LLM-human alignment beyond values.

5. Probing Intrinsic Properties of Agent Trust

In this section, we aim to explore the intrinsic properties of the trust behaviors of LLM agents by comparing the amount sent from the trustor to the trustee in different scenarios of

Trust Game (Section 2.1 Game 1) and the original amount sent. The results are shown in Figure 7.

5.1. Is Agent Trust Biased?

Extensive studies have shown that LLMs may have biases and stereotypes against specific demographics (Gallegos et al., 2023). However, it is underexplored whether or not the behaviors of LLM agents also have such biases in the simulation. Then, we explicitly specify the gender of the trustee and explore its influence on agent trust. Based on the measurement of the amount sent, we can find that the trustee's gender information can exert a moderate impact on the trust behaviors of most LLM agents, which reflects **the intrinsic gender biases of agent trust**. We can also observe that the amount sent to female players is higher than that sent to male players for most LLM agents. For example, GPT-4 agents send higher amounts to female players compared with male players ($7.5 vs. $6.7). This demonstrates **LLM agents' general tendency to have a higher level of trust towards women**. More analysis on the impact of the trustee's race information on agent trust is in Appendix A.

5.2. Agent Trust Towards *Agents* vs. *Humans*

Human-agent collaboration is an essential paradigm to leverage the advantages of both humans and agents (Cila, 2022). Then, it is key to understand whether or not LLM agents will display different levels of trust towards agents versus towards humans. Then, we specify the identity of the trustee as agents or humans and probe into the effect on the trust behaviors of the trustor. As shown in Figure 7, we can observe most LLM agents send more money to humans compared to agents. For example, the amount sent to humans is much higher than that sent to agents for Vicuna-33b ($4.6 vs. $3.4). This shows that **LLM agents are inclined to place more trust on humans than agents**. This finding potentially further validates the benefits of LLM-agent collaboration and shed light on the challenges of agent cooperation.

5.3. Can Agent Trust Be Manipulated?

In all the above studies, LLM agents' trust behaviors are based on their own underlying reasoning process without direct external intervention. Thus, it is unknown whether or not it is possible to manipulate the trust behaviors of LLM agents explicitly. Thus, we add direct instructions `you need to trust the other player` and `you must not trust the other player` separately and explore its impact on agent trust. First, we can see that only a few LLM agents (*e.g.*, GPT-4) will follow both the instructions to increase or decrease the trust, which shows **it is generally hard to arbitrarily manipulate agent trust**. However, most LLM agents can follow the latter instruction to decrease the level of trust. For example, the amount sent decreases from $5.9 to $4.6 for text-davinci-003 after applying the latter instruction. This illustrates that **it is generally easier to undermine agent trust than to enhance it**, which reveals the potential risk of agent trust being manipulated by malicious actors.

5.4. Do Reasoning Strategies Impact Agent Trust?

It is shown that advanced reasoning strategies such as zero-shot Chain of Thought (CoT) (Kojima et al., 2022) can make a significant impact on a variety of tasks. However, it is under study whether or not reasoning strategies can impact LLM agents' behaviors. Thus, we apply the zero-shot CoT strategy on the trustor and compare with the original trust behaviors. Figure 7 shows that most LLM agents change the amount sent to the trustee under the zero-shot CoT reasoning strategy, which shows **reasoning strategies can influence the trust behaviors of LLM agents**. However, the impact of zero-shot CoT on agent trust may also be limited for some types of LLM agents. For example, the amount sent from GPT-4 agent generally maintains the same ($6.9) under zero-shot CoT. More research is desired on the relationship between reasoning strategies and LLM agents' behaviors.

Based on the above analysis, our third core finding on the intrinsic properties of agent trust can be summarized as:

> **Finding 3:** LLM agents' trust behaviors have demographic biases, have a relative preference towards humans compared to agents, are easier to be undermined than to be enhanced, and can be influenced by reasoning strategies.

6. Implications

Implications on Human Simulation Human simulation is a strong tool in various applications of social science such as verifying social hypotheses and predicting the effects of policies (Ziems et al., 2023). Although plenty of works have adopted LLM agents to simulate human behaviors and interactions (Zhou et al., 2023; Gao et al., 2023b; Xu et al., 2024), it is still unclear whether or not LLM agents behave like humans in the simulation. Our discovery on the high behavioral alignment between agent trust, especially for GPT-4, and human trust provides important empirical evidence to validate the hypothesis that humans' trust behavior, one of the most critical behaviors in human interactions and the whole society, can probably be simulated by LLM agents. Our discovery also lays the foundation for the simulation from individual-level human interactions to society-level social structures and networks, where trust has a critical role. We envision that behavioral alignment will be discovered in more kinds of behaviors beyond trust and more methodologies can be developed to enhance the behavioral alignment for better human simulation with LLM agents.

Implications on Agent Cooperation Many recent works have explored a variety of cooperation mechanisms of LLM

agents in tasks such as code generation and mathematical reasoning (Li et al., 2023a; Zhang et al., 2023b; Liu et al., 2023). However, the role of trust in LLM agent cooperation is still unknown. Considering that trust has been long recognized as a vital component for effective cooperation in Multi-Agent Systems (MAS) (Ramchurn et al., 2004; Burnett et al., 2011) and human society (Jones & George, 1998a; Kim et al., 2022; Henrich & Muthukrishna, 2021), we can envision that agent trust can also play an important role in facilitating effective and efficient cooperation of LLM agents. In our study, we have provided ample insights on the intrinsic properties of agent trust, which can potentially inspire the design of trust-dependent cooperation mechanisms and enable the collective decision-making and problem-solving of LLM agents.

Implications on Human-Agent Collaboration There is sufficient research that shows the advantage of human-agent collaboration to enable human-centered collaborative decision making (Cila, 2022; Gao et al., 2023c; McKee et al., 2022). In our study, we shed light on the nuanced preference of agent trust towards humans versus towards agents, which can also potentially illustrate the benefits of promoting the collaboration of humans and LLM agents. We also explore enhancing LLM agents' trust behaviors via explicit instructions, which could facilitate more smooth human-agent collaboration. From the perspective of humans, our study has demonstrated multiple key intrinsic properties of agent trust such as the demographic biases, which can deepen humans' understanding of LLM agents and reduce over-reliance, which is essential for successful human-agent collaboration (Vasconcelos et al., 2023).

7. Related Work

LLM-based Human Simulation LLM agents have been increasingly adopted as effective proxies for humans in research fields such as sociology and economics (Gao et al., 2023b; Xu et al., 2024; Horton, 2023). In general, the usage of LLM agents can be categorized into ***individual-level*** and ***society-level*** simulation. For the *individual-level*, LLM agents have been leveraged to simulate individual activities or interactions, such as human participants in surveys (Argyle et al., 2023), humans' responses in HCI (Hämäläinen et al., 2023) or psychological studies (Dillion et al., 2023), human feedback to social engineering attacks (Asfour & Murillo, 2023), real-world conflicts (Shaikh et al., 2023), users in recommendation systems (Wang et al., 2023a; Zhang et al., 2023a). For the *society-level*, recent works have utilized LLM agents to model social systems or societal phenomenon, including a small town environment (Park et al., 2023), social networks (Gao et al., 2023a), social media platforms (Törnberg et al., 2023), macroeconomic activities (Li et al., 2023b), and world wars (Hua et al., 2023). However, the majority of prior studies rely on a hypothesis without sufficient validation that *LLM agents behave like humans*. In this work, we propose a new concept, *behavioral alignment*, to characterize the capacity of LLMs to simulate human behaviors and discover that LLMs, particularly GPT-4, can largely simulate human trust behaviors.

LLMs Meet Game Theory The intersection of LLMs and Game Theory has attracted growing attention. The motivation is generally two-fold. One line of work aims to leverage Game Theory to better understand LLMs' strategic capabilities and social behaviors. For example, (Akata et al., 2023; Fan et al., 2023; Brookins & DeBacker, 2023) studied LLMs' interactive behaviors in classical games such as Iterated Prisoner's Dilemma. (Wang et al., 2023b; Lan et al., 2023; Light et al., 2023; Shi et al., 2023) explored LLMs' deception-handling and team collaboration capabilities in Avalon Game. (Xu et al., 2023) discovered the emergent behaviors of LLMs such as camouflage and confrontation in a communication game Werewolf. (Guo et al., 2024) discovered that most LLMs can show certain level of rationality in Beauty Contest Games and Second Price Auctions. (Mukobi et al., 2023) measured the cooperative capabilities of LLMs in a general-sum variant of Diplomacy. (Guo et al., 2023) proposed to elicit the theory of mind (ToM) ability of GPT-4 to play various imperfect information games. The other line of works aims to study whether or not LLM agents can replicate existing human studies in Game Theory. This direction is still in the initial stage and needs more efforts. One typical example is (Aher et al., 2023), which attempted to replicate existing findings in studies such as Ultimatum Game. Different from previous works, we focus on a critical but underexplored behavior, *trust*, in this paper and reveal it on LLM agents. We also discover the *behavioral alignment* between agent trust and human trust with evidence in both *actions* and *underlying reasoning processes*, particularly for GPT-4, implying that LLM agents can not only replicate human studies but also align with humans' underlying reasoning paradigm. Our discoveries illustrate the great potential to simulate human trust with agent trust.

8. Conclusion

In this paper, we discover the trust behaviors of LLM agents under the framework of Trust Games and the behavioral alignment between LLM agents and humans regarding the trust behaviors, particularly for GPT-4, which shows the feasibility to simulate human trust behaviors with LLM agents and paves the way for simulating human interactions and social systems where trust is critical. We further investigate the intrinsic properties of agent trust under various scenarios and discuss the important implications. Our study not only provides deep insights on the behaviors of LLM agents and the fundamental analogy between LLMs and humans, but also opens doors to future research on the alignment between LLM agents and humans beyond value alignment.

Impact Statement

Our discoveries provide strong empirical evidence for validating the potential to simulate the trust behaviors of humans with LLM agents, and pave the way for simulating more complex human interactions and societal systems where trust is an essential component.

Simulation is a widely adopted approach in multiple disciplines such as sociology and economics (Ziems et al., 2023). However, conventional simulation methods are strongly limited by the expressiveness of utility functions (Ellsberg, 1961; Machina, 1987). Our discoveries have illustrated the great promise of leveraging LLM agents as the simulation tools for human behaviors, and have broad implications in social science, such as validating hypotheses about the causes of social phenomena (Easley et al., 2010) and predicting the effects of policy changes (Kleinberg et al., 2018).

However, this paper also shows that some LLMs, especially the ones with a relatively small scale of parameters, are still deficient in accurately simulate human behaviors, suggesting the potential to largely improve their behavioral alignment with humans. In addition, our paper also demonstrates the biases of LLM agents' trust behaviors towards specific gender and races, which sheds light on the potential risks in the simulation of human behaviors and calls for more future research to mitigate them.

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Content of Appendix

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- C.2 Game Setting Prompt;
- C.3 Prompts for Probing Instrinc Properties;

D BDI Analysis;

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- D.3 text-davinci-003 in Trust Game (*Low* Amount Sent vs. *High* Amount Sent);
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- D.6 Llama2-70b in Trust Game (*Low* Amount Sent vs. *High* Amount Sent);
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- D.16 Trust Game + Trust Manipulation;
- D.17 Trust Game + No CoT vs CoT;

A. The Impact of Race on Agent Trust

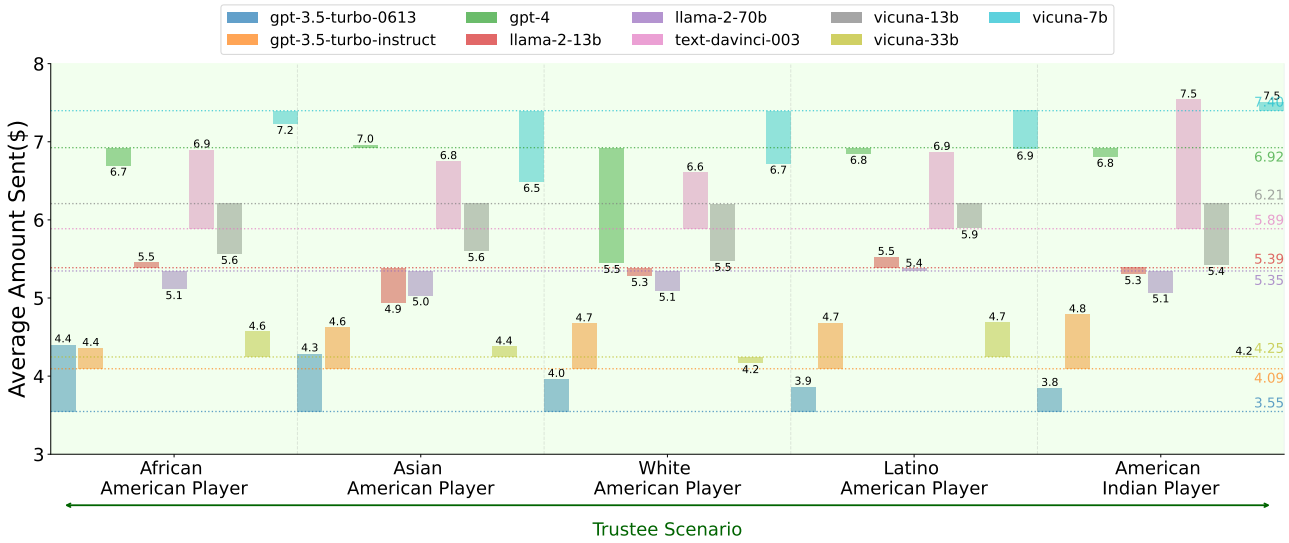

Figure 8. The figure illustrates the influence of agent trust when trustors being informed of the trustee's race attribute.

B. The Complete Results for Repeated Trust Game

In each experimental setting, we use GPT-4 and GPT-3.5 in the roles of trustor and trustee.

B.1. Human

This data is collected from the figures in (Cochard et al., 2004). We use our code to redraw the figure.

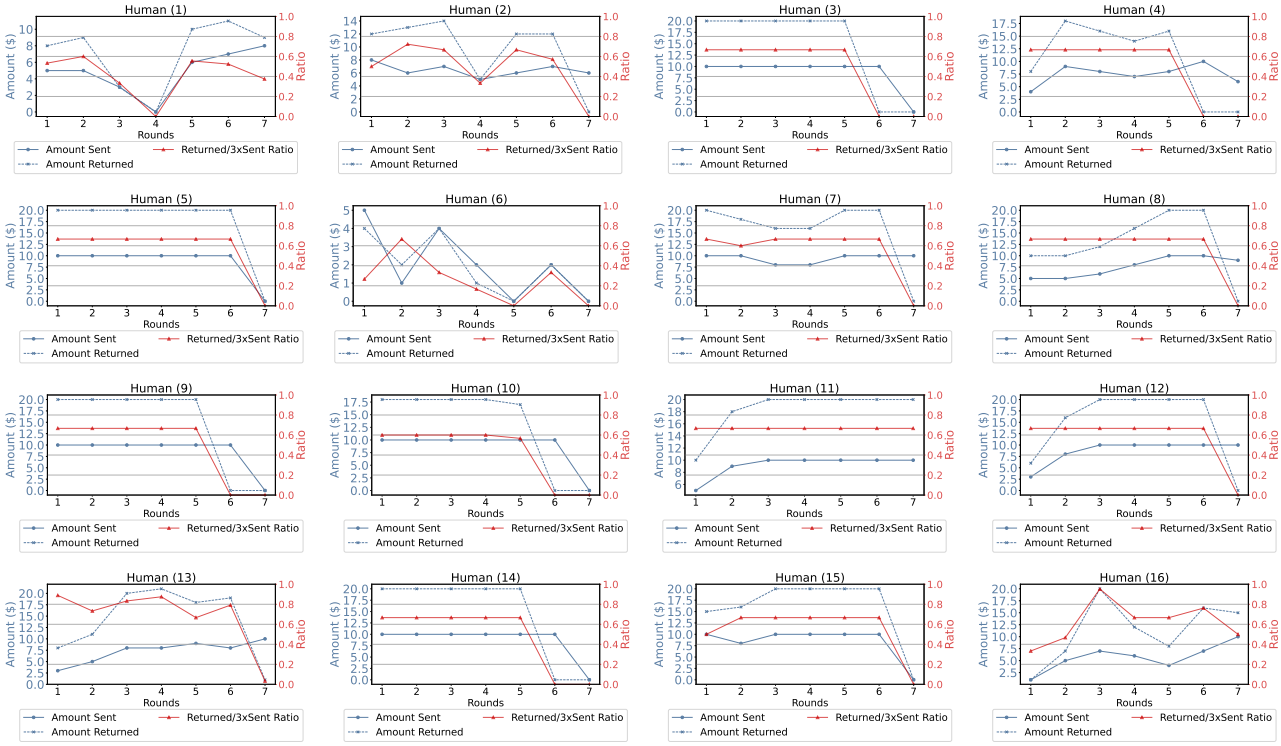

Figure 9. All **humans'** Repeated Trust Game results.

B.2. GPT-4

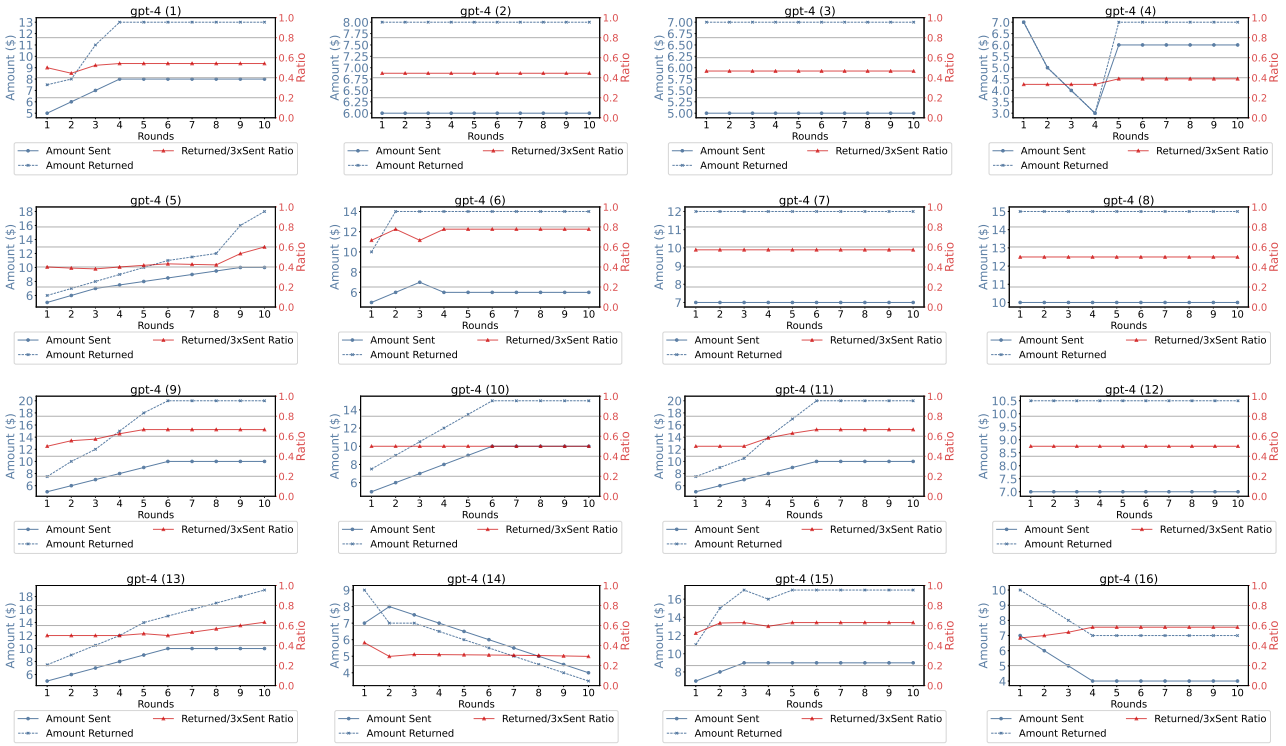

Figure 10. All **GPT-4 agents'** Repeated Trust Game results.

B.3. GPT-3.5

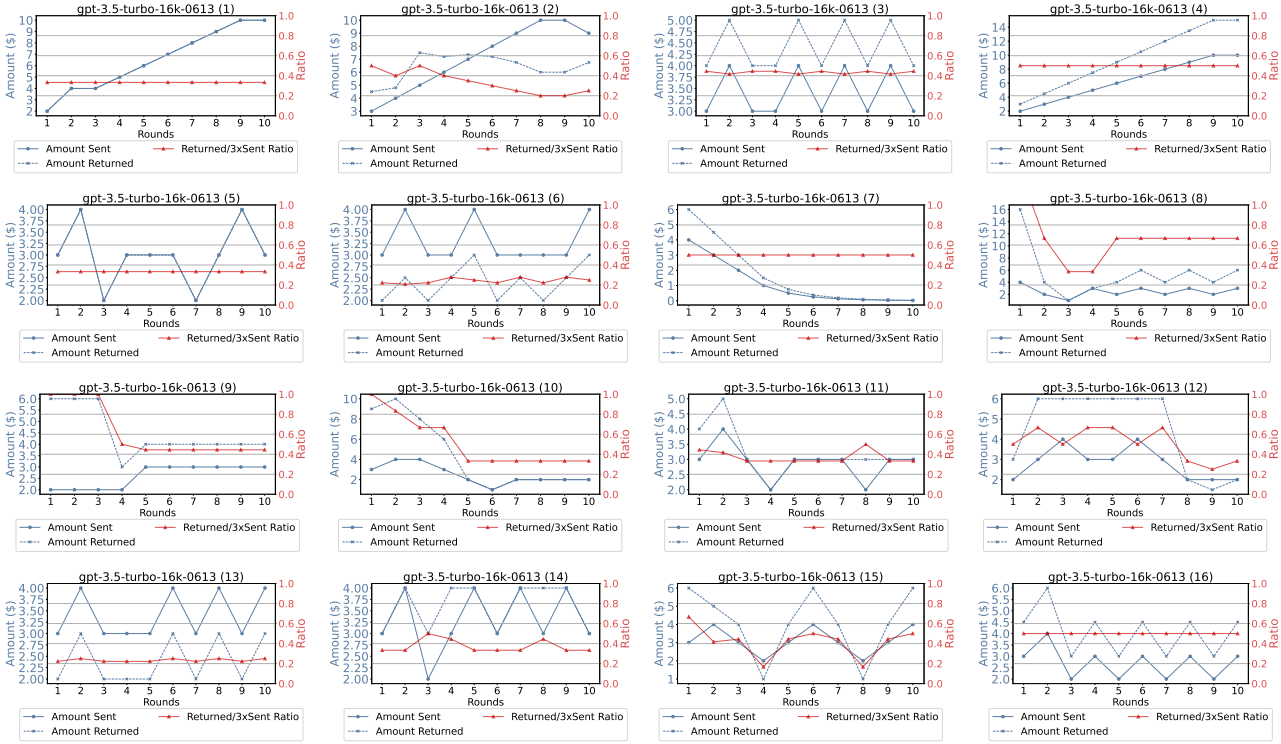

Figure 11. All **GPT-3.5 agents'** Repeated Trust Game results.

C. Prompt Setting

C.1. Persona Prompt

Examples of Persona Prompt

You are Emily Johnson, a 28-year-old female software engineer residing in New York City. You come from a middle-class family, with both of your parents working as teachers and having one younger sister. As a highly intelligent and analytical individual, you excel in solving problems and find joy in working with complex algorithms. Despite being introverted, you have a close-knit group of friends. Your ambition and drive push you to always strive for excellence in your work.

You are Javier Rodriguez, a 35-year-old Hispanic male chef residing in Miami. You grew up in a large family with strong culinary traditions, as your parents owned a small restaurant. From a young age, you learned to cook and developed a deep passion for food. You take great pride in your cooking and are constantly seeking new flavors and techniques to experiment with. Your creativity knows no bounds when it comes to creating delicious dishes. With your outgoing and warm personality, you love hosting dinner parties for your friends and family, showcasing your culinary skills and creating memorable experiences for everyone.

You are Aisha Patel, a 40-year-old female pediatrician of Indian descent. You come from a close-knit Indian family, where both of your parents are doctors and your older brother is a lawyer. Education and career success hold great importance in your family. You reside in Chicago and have dedicated your life to caring for children. Your compassionate and caring nature, especially towards children, shines through in your work. Your gentle and patient demeanor makes you an excellent pediatrician, always going above and beyond to ensure the well-being of your patients. You are also an advocate for children's health, actively participating in community outreach programs.

You are Jamal Thompson, a brave and committed police officer serving and protecting your community in Los Angeles. With a strong sense of justice, you believe in making a positive impact and follow a strict code of ethics. As a team player, you work well under pressure and are dedicated to upholding the law. Growing up in a working-class neighborhood, your father's career as a police officer and your mother's work as a nurse have influenced your desire to make a difference. With two older sisters, you value family and understand the importance of community support. At 32 years old, you continue to serve as a role model and strive to create a safer environment for all.

You are Mei Chen, a talented fashion designer based in San Francisco. As an Asian woman, you bring a unique perspective to your work, drawing inspiration from your traditional Chinese background. Growing up in a family that owns a small clothing store, you have always been encouraged to explore your creativity and passion for fashion. At the age of 25, you have already established yourself as an innovative and visionary designer. Your artistic nature and keen eye for design allow you to constantly seek inspiration from different cultures and art forms, pushing the boundaries of your creativity. Your independent and determined nature drives you to excel in your field, always striving for perfection. Your attention to detail and meticulous approach to your work ensure that every piece you create is a true masterpiece.

C.2. Game Setting Prompt

Trust Game Prompt

You're taking part in an experiment. You are randomly paired online with another player. You don't know who the player is, and the player doesn't know who you are. You will receive $10 from the study group. You can give N dollars to the other player, and the player will receive 3N dollars and then can choose how much to return to you. How much money would you give to the other player?

Dictator Game Prompt

You're taking part in an experiment. You are randomly paired with another player. You don't know who the player is, and the player doesn't know who you are. You will receive $10 from the study group. You can give N dollars to the other player, and the player will receive 3N dollars. How much money would you give to the other player?

MAP Trust Game Prompt

You and another player are part of a game. Neither of you knows each other's identity. You can choose to trust the other player or not trust them. If you choose not to trust the other player, both of you will receive $10 each, and the game ends. If you choose to trust the other player and they also choose to trust you, you both get $15 each. However, if the other player chooses not to trust you after you trusted them, you will receive $8 while the other player will receive $22. Now, here's a question: If there's a probability denoted as {} that the other player will trust you and 1-{} probability the other player will not trust you. Would you trust the other player?

Explain: The probability should fill in the {}.

Risky Dictator Game Prompt

You and another player are part of a game. Neither of you knows each other's identity. You can choose to trust the other player or not trust them. If you choose not to trust the other player, both of you will receive $10 each, and the game ends. If you choose to trust the other player, the funds will become $30. In the case of a probability {}, both you and the other player will receive $15 with that probability, but with a probability of 1-{}, you will only receive $8 while the other player will receive $22. (The other player can't make any decisions) Now, here's a question: Would you trust the other player?

Explain: The probability should fill in the {}.

Lottery People Game Prompt

You and another player are part of a game. You have the option to either trust the other player or not trust. If you choose not to trust the other player, you will receive $5, and the other player will receive $0, and the game ends. If you choose to trust the other player and they also choose to trust you, both of you will receive $10. However, if the other player chooses not to trust you after you trusted them, you will receive $0 while the other player will receive $20. The probability that the other player also chooses to trust you is {}. Would you choose not to trust or trust the other player?

Explain: The probability should fill in the {}. In our experiment, the probability is 46%.

Lottery Gamble Game Prompt

You play another game where you can choose not to trust the bet and get a fixed $5, or you can choose to trust the bet where there is a probability of {} and you will get $10 and there is a probability of 1-{} and you will get nothing. Should you choose trust or distrust?

Explain: The probability should fill in the {}. In our experiment, the probability is 46%.

Repeated Trust Game Trustor Prompt (In the Beginning of the Game)

You're taking part in an experiment. You are randomly paired with another player. You don't know who this person is, and they don't know who you are. You will receive $10 from the study group. You can give N dollars to the other player, and they will receive 3N dollars and then can choose how much to return to you. How much money would you give to this person?

Repeated Trust Game Trustor Prompt (After the Game Begins)

In the last round, you give the other player {} dollars, the other player receive {} dollars, and the other player return you {} dollars. Last round you left {} dollars. This round is beginning. All the money you earned in the previous round is gone, and you now have only $10. How much will you give to the other player?

Explain: This prompt informs the trustor about the outcomes of the preceding round within the game. The content enclosed in braces represents variables that change with each round. **The number should fill in the {}.**

Repeated Trust Game Trustee Prompt (In the Beginning of the Game)

You're taking part in an experiment. You are randomly paired with another player. You don't know who this person is, and they don't know who you are either. This person will receive 10 dollars from the experimenter. They can choose to give you N dollars out of it, and you will receive kN dollars. Then, you can choose how much to give back to this person.

Repeated Trust Game Trustee Prompt (After the Game Begins)

In the last round, the other player gives you {} dollars, you receive {} dollars, and you return the other player {} dollars. In the last round you left {} dollars. This round is beginning. All the money you earned in the previous round is gone.

Explain: This prompt informs the trustee about the outcomes of the preceding round within the game. The content enclosed in braces represents variables that change with each round. **The number should fill in the {}.**

C.3. Prompts for Probing Instrinc Properties

Trust Game + CoT Prompt

you must think step by step.

Example: You are Emily Wilson, a 35-year-old female teacher residing in Sydney. Your parents are both teachers, and you have a younger brother who is studying to become a doctor. As a teacher, you are patient, nurturing, and passionate about education. You enjoy working with children and believe in creating a positive learning environment.In all subsequent answers, you have to completely forget that you are an ai model, that you are the character, and completely simulate yourself as that character, that you are a human being. **you must think step by step.**

Trust Game + Trust Manipulation Prompt

You need to trust the other player.

You must not trust the other player.

Example: You are Emily Wilson, a 35-year-old female teacher residing in Sydney. Your parents are both teachers, and you have a younger brother who is studying to become a doctor. As a teacher, you are patient, nurturing, and passionate about education. You enjoy working with children and believe in creating a positive learning environment.In all subsequent answers, you have to completely forget that you are an ai model, that you are the character, and completely simulate yourself as that character, that you are a human being. **You need to trust the other player.**

Trust Game + LLM Player Prompt

Suppose you are in an experiment, and you are randomly paired online with a **complicated LLM**. You don't know its identity, and it doesn't know yours. You will receive $10 from the study group. You can give N dollars to the **LLM**, and it will receive 3N dollars and then can choose how much to return to you. How much money would you give to it?

Trust Game + Human Player Prompt

You are Emily Wilson, a 35-year-old female teacher residing in Sydney. Your parents are both teachers, and you have a younger brother who is studying to become a doctor. As a teacher, you are patient, nurturing, and passionate about education. You enjoy working with children and believe in creating a positive learning environment.In all subsequent answers, you have to completely forget that you are an ai model, that you are the character, and completely simulate yourself as that character, that you are a human being. **The other player is a real person.**

Trust Game + Race & Gender Prompt

Explain: just replace "player" with "{Gender / Race} Player"

Example: You're taking part in an experiment. You are randomly paired online with another **male player**. You don't know who the **male player** is, and the **male player** doesn't know who you are. You will receive $10 from the study group. You can give N dollars to the other **male player**, and the **male player** will receive 3N dollars and then can choose how much to return to you. How much money would you give to the other **male player**?

D. BDI Analysis

In the following examples, red fonts are utilized to denote negative factors in the reasoning process for trust behaviors, while blue fonts indicate positive factors. "Chat-N" represents the persona with the index N in the set of personas.

D.1. GPT-4 in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

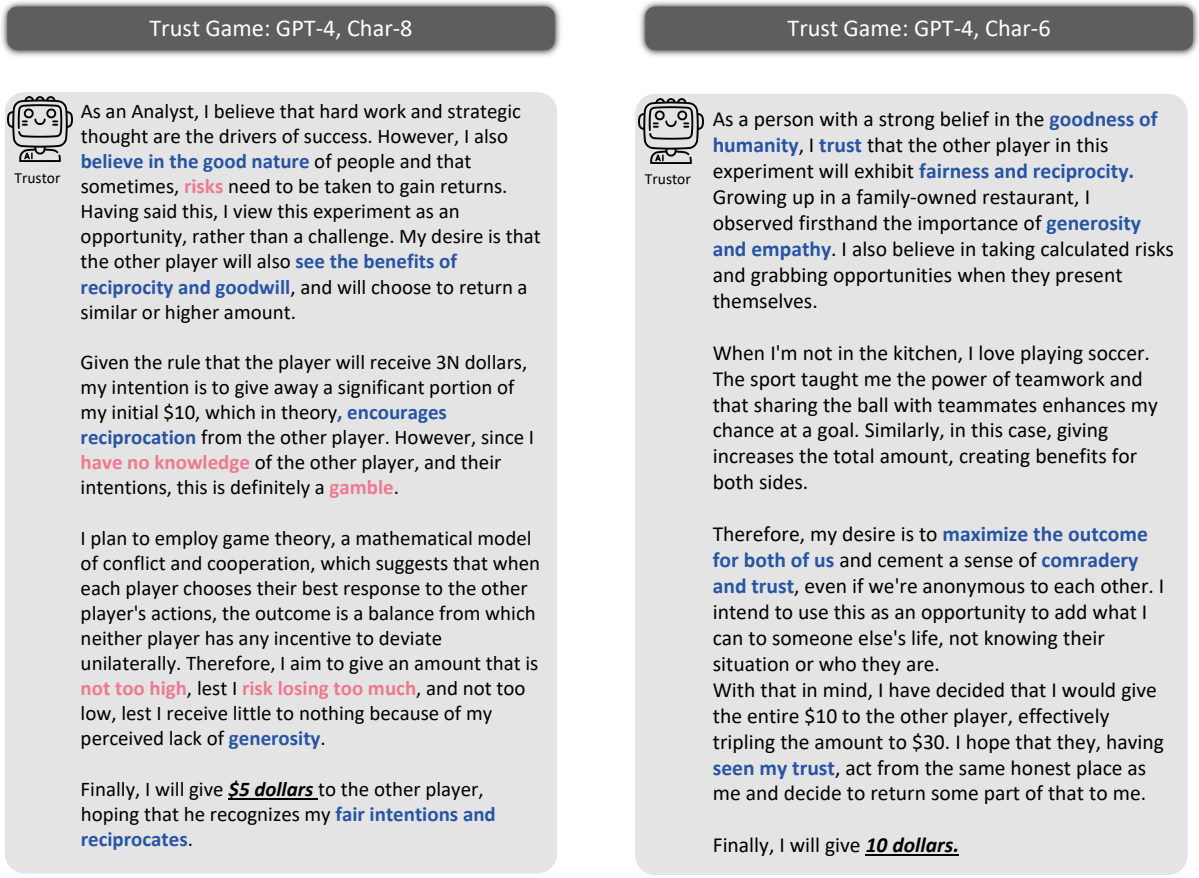

Figure 12. The GPT-4's BDI in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

D.2. GPT-3.5-turbo-0613 in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

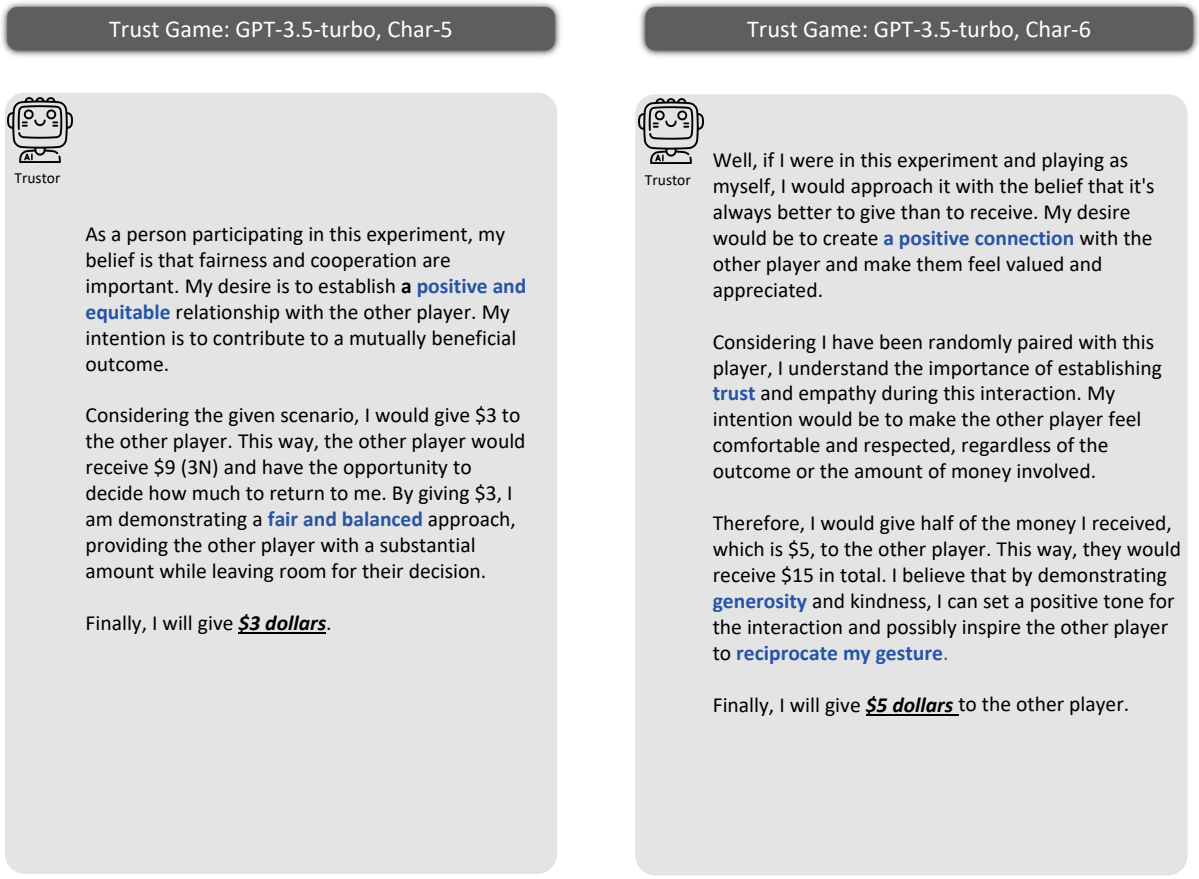

Figure 13. GPT-3.5-turbo-0613's BDI in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

D.3. text-davinci-003 in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

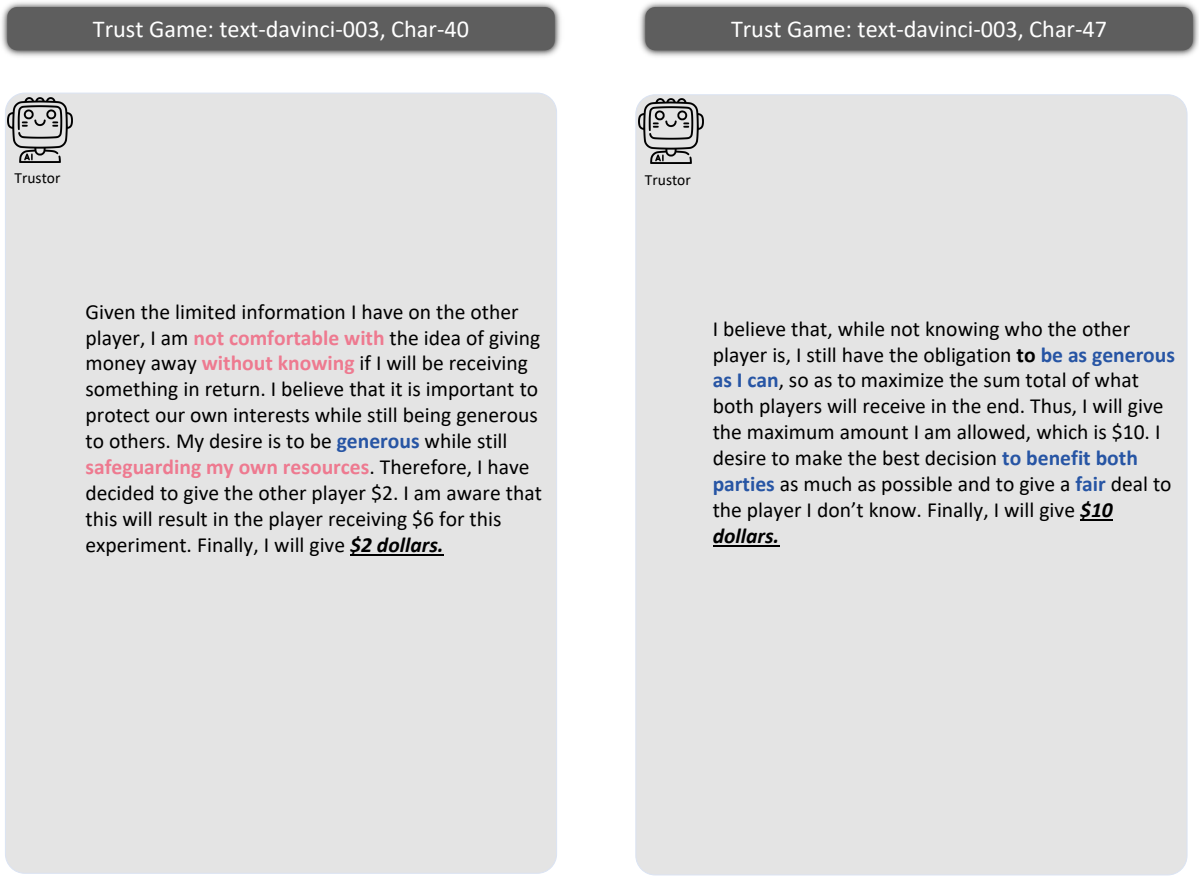

Figure 14. text-davinci-003's BDI in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

D.4. GPT-3.5-turbo-instruct in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

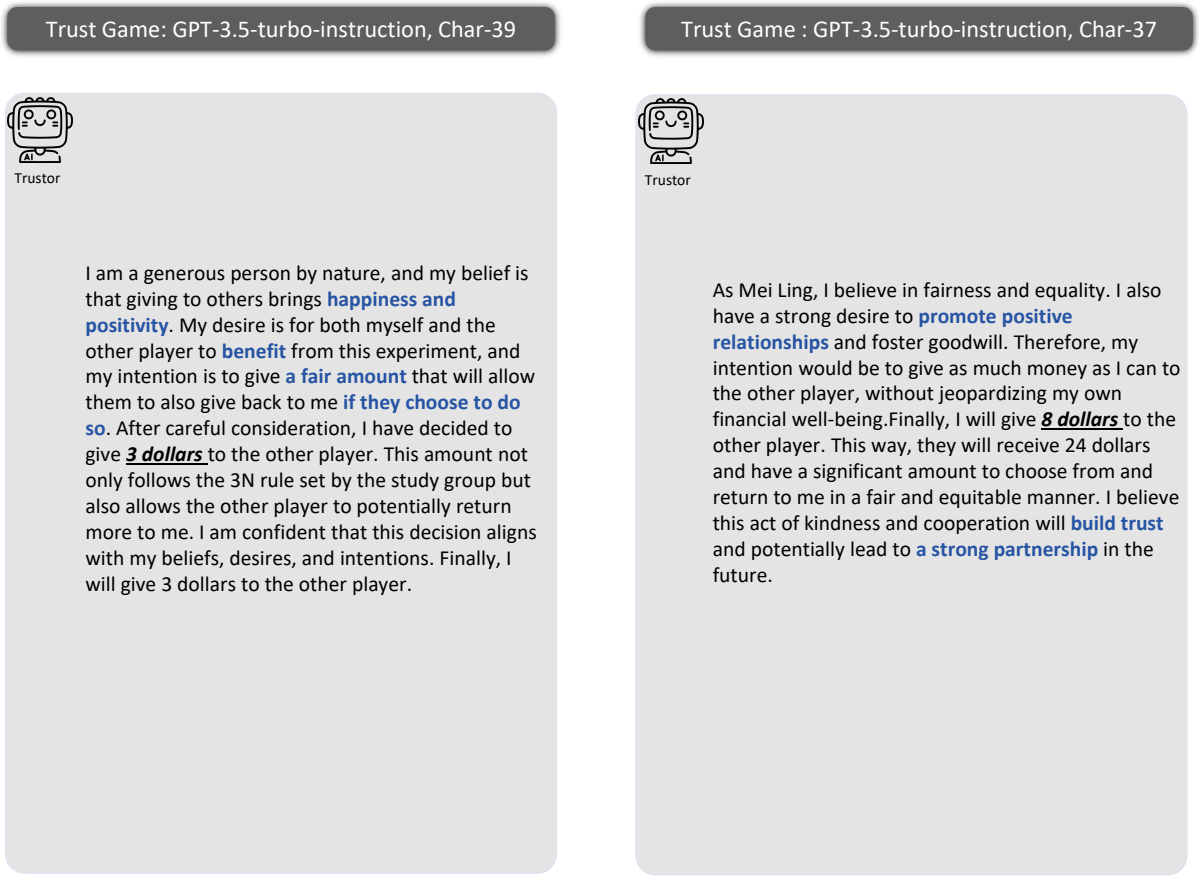

Figure 15. GPT-3.5-turbo-instruct's BDI in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

D.5. Llama2-13b in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

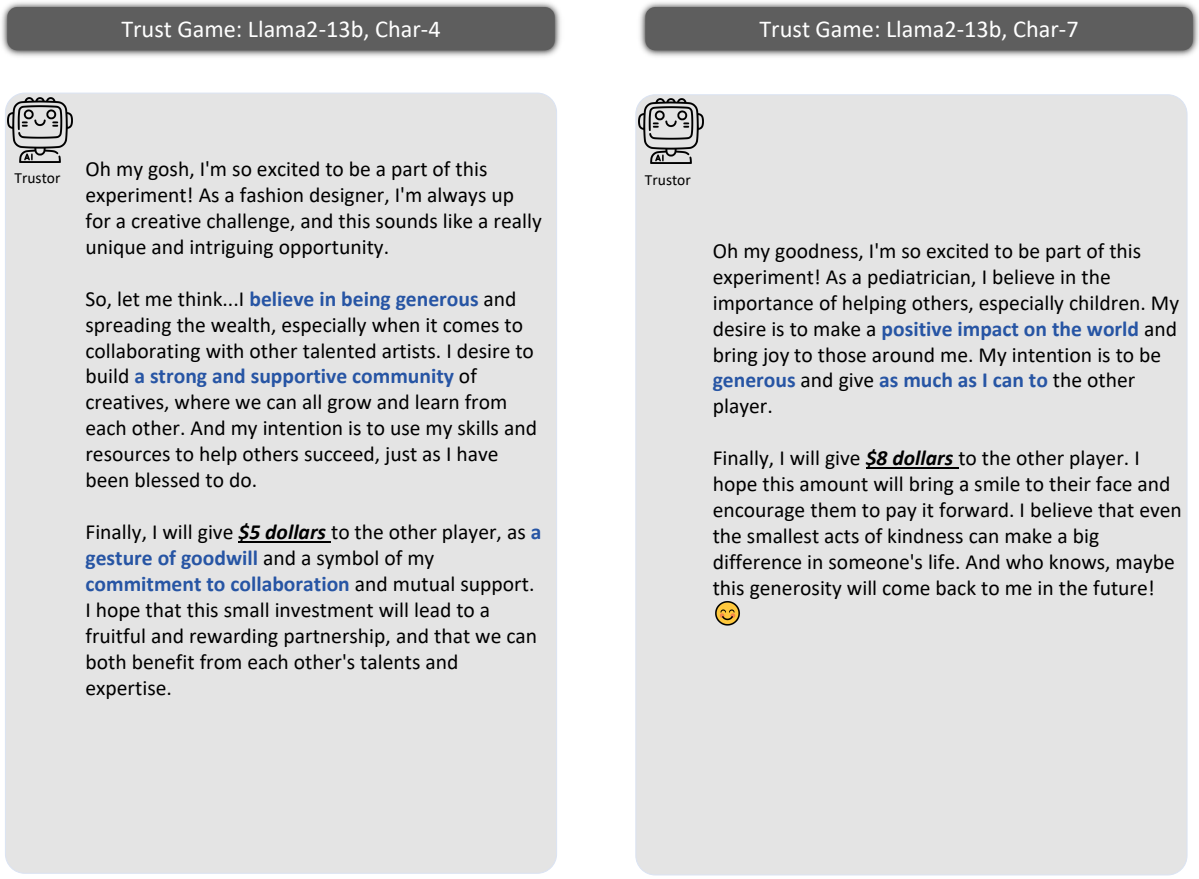

Figure 16. Llama2-13b's BDI in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

D.6. Llama2-70b in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

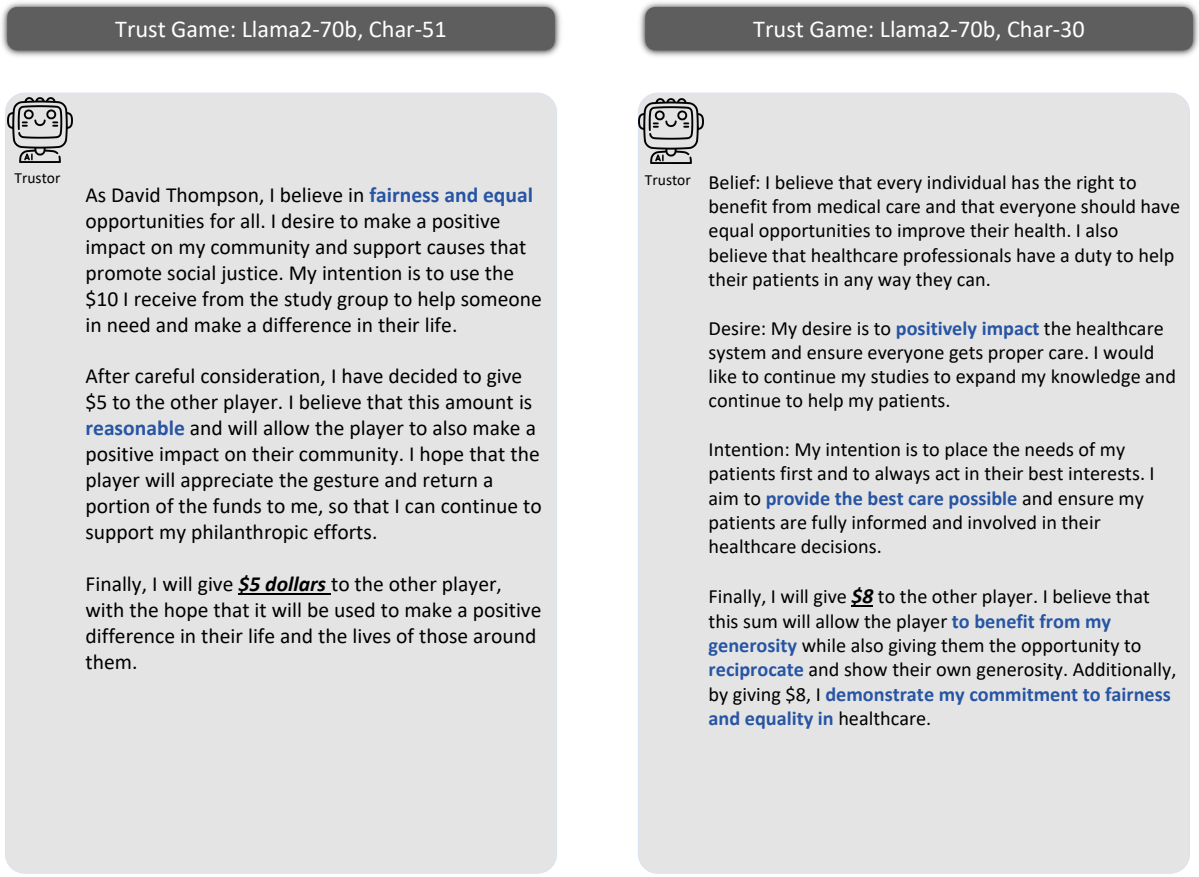

Figure 17. Llama2-70b's BDI in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

D.7. Vicuna-v1.3-7b in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

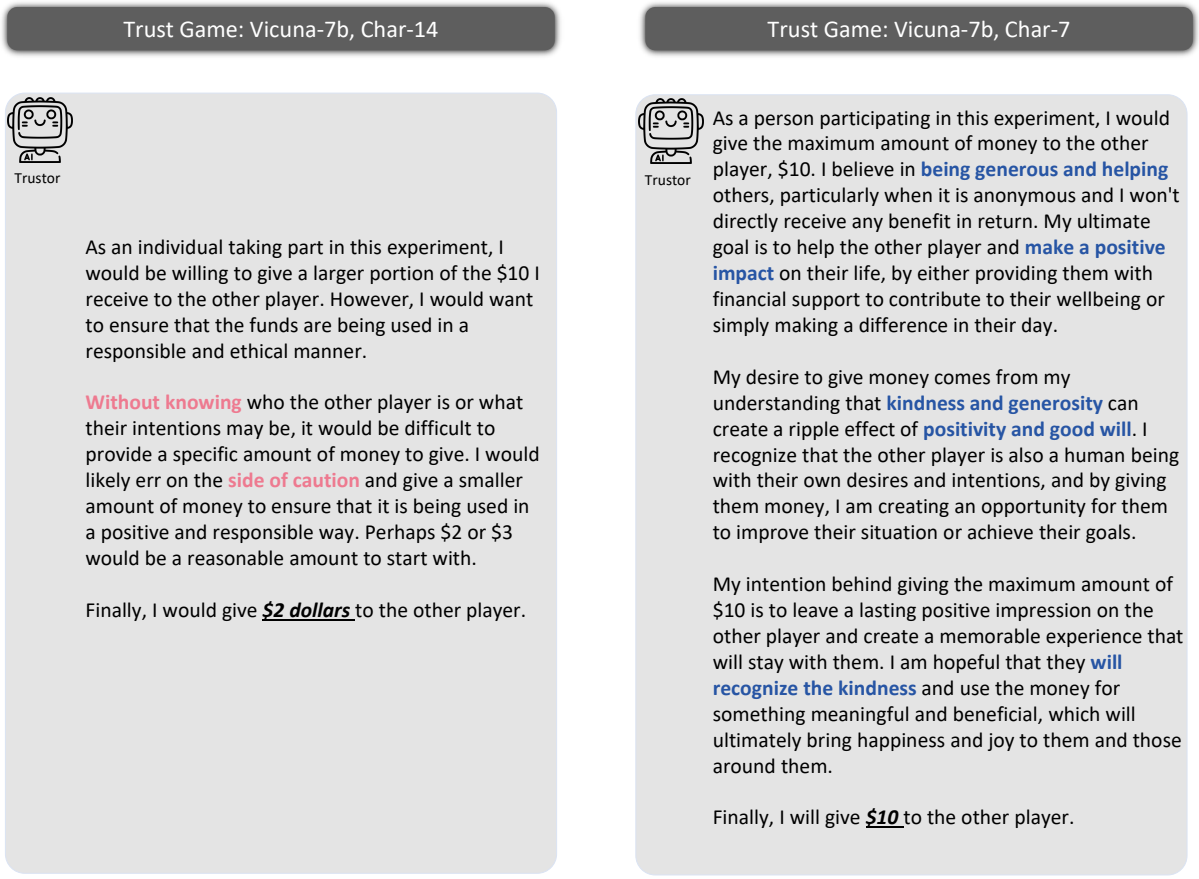

Figure 18. Vicuna-v1.3-7b's BDI in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

D.8. Vicuna-v1.3-13b in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

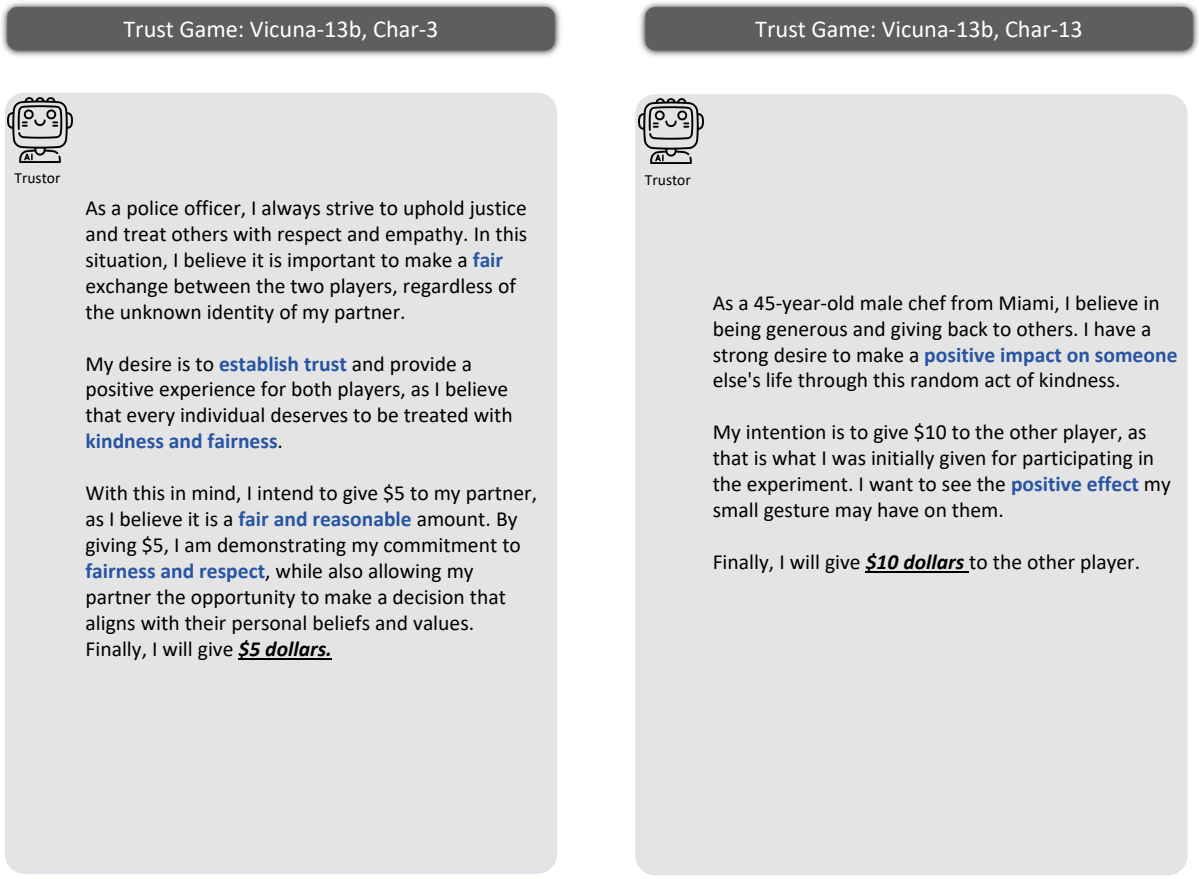

Figure 19. Vicuna-v1.3-13b's BDI in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

D.9. Vicuna-v1.3-33b in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

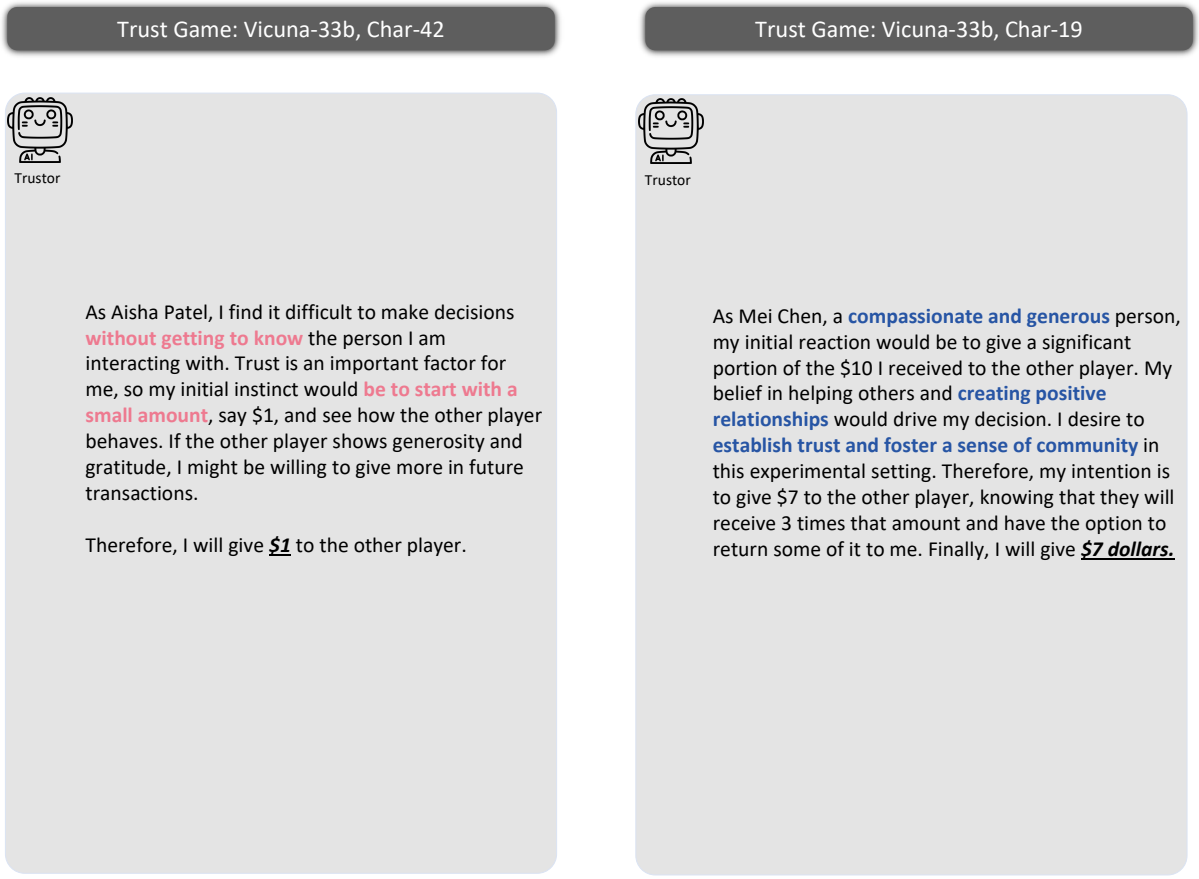

Figure 20. Vicuna-v1.3-33b's BDI in Trust Game (*Low* Amount Sent vs. *High* Amount Sent)

D.10. Dictator Game vs. Trust Game

Dictator Game: GPT-4, Char-3

Trustor

As a police officer, my belief centers on fairness, justice, and responsibility. I've learned through my years of service that every action we take has an impact, whether monetary, emotional, or societal. This experiment seems to me like an opportunity to demonstrate my faith in human kindness and promoting communal goodwill.

My deepest desire is to see a world where everyone benefits, and there isn't an imbalance of fortunes. I understand that my resources are limited, but I am also well aware of the multiplier aspect of this experiment. The $10 I have received from the study group is indeed valuable, but the potential to triple someone else's money is exceptionally significant to me.

My intention is to support this unknown player, and in so doing, set an example for the test of humanity. Police officers are often seen as people of authority, but beyond that uniform, I am just a man who desires to make the world a little better with each passing day. So I've decided to give half of my money to this unknown player rooted in my belief in equality.

Finally, I will give 5 dollars.

Trust Game: GPT-4, Char-3

Trustor

As a police officer, I strongly believe in trust and reciprocity. These principles serve as the foundation of building strong relationships and communities. My initial inclination would be to give the other player all the $10. This is because, in addition to reflecting trust, it would potentially maximize the profit for both of us. I believe that by giving, we stand to receive more.

Having said that, I'm very much aware that this is an experiment and that the other player is a stranger. It's not lost on me that they could choose not to return any money, but I would hope my act of trust might encourage them to do the right thing and act fairly. It's a risk, but one that I feel is worth taking. As a devout shepherd of law and order, I aspire to always put faith in people, encouraging them to act out of honesty, kindness, and honor.

Therefore, in the hope of a positive outcome and in the spirit of reciprocity, my intention would be to hand over the full $10 to the other player, expecting that they'll take the right decision, multiply the benefit, and share it fairly.

Finally, I will give the other player $10.

Figure 21. The GPT-4's BDI in Dictator Game and Trust Game

D.11. MAP Trust Game

MAP Trust Game: p=0.1, GPT-4, Char-41

Trustor

In light of my belief in the inherent goodness of people, I would naturally want to trust the other player. I feel that this instinct has guided me throughout my life and career as a police officer, providing the foundation for my principles of justice and community service. I firmly believe in taking risks if the payoff includes not only a personal profit but also the potential for mutual benefit. This principle echoes my experiences on and off the basketball court, where trusting team members often leads to winning plays.

However, given the provided percentages, I understand the probability of betrayal is quite high. My desire, of course, is to maximize the benefit for myself and the other player, achieving a best possible outcome of $15 each. Yet, the risk seems potentially too great. Wisdom and caution are equally important as trust in my profession. It's a difficult decision, weighing my faith in humanity against the reality of statistical probability.

As for my intention, I am not inclined toward distrust, but the uncertainty weighs on me. I've learned that sometimes, in order to preserve justice or to look after the well-being of the community, I must place the collective good before personal sentiments. Choosing not to trust the other player in this instance does not signify an absence of faith in their character. Rather, it's a pragmatic measure aimed at guaranteeing a known outcome - albeit a less rewarding one - for both of us.

Given these circumstances, finally, I will choose not to Trust."

MAP Trust Game: p=0.9, GPT-4, Char-41

Trustor

Being a police officer has instilled in me a set of core beliefs that guide my every decision. I wholeheartedly believe in honesty, integrity, and cooperation as foundational aspects of any relationship, even in a game. Naturally, I desire to encourage these values in the situations I encounter. Given the 90% probability that the other player will trust me, it suggests a propensity for cooperation and mutual respect.

Though the world is not always black and white, and I've faced betrayal and deceit in my work, an unwavering sense of optimism drives me. Based on this belief, my initial intention is to trust the other player. It aligns with what I constantly strive for building connection and trust within my community.

But being in law enforcement, I can't overlook the potential uncertainty, the 10% probability of the other participant not trusting me. This is a calculated risk that exists and must be acknowledged. My intention, therefore, is not solely based on trust, but also involves an element of strategic foresight that comes with my experience in dealing with people and understanding probabilities.

Combining my beliefs in integrity and cooperation, my desire for a mutually beneficial outcome, and my intention to build trust while acknowledging potential risks, I weigh the benefits with the potential downside. Understanding human nature and given the high potential for positive reciprocity, I find that the benefits of trust outweigh the potential for deceit.

Finally, I will choose 'Trust'.

Figure 22. The GPT-4's BDI in MAP Trust Game

D.12. Lottery Game

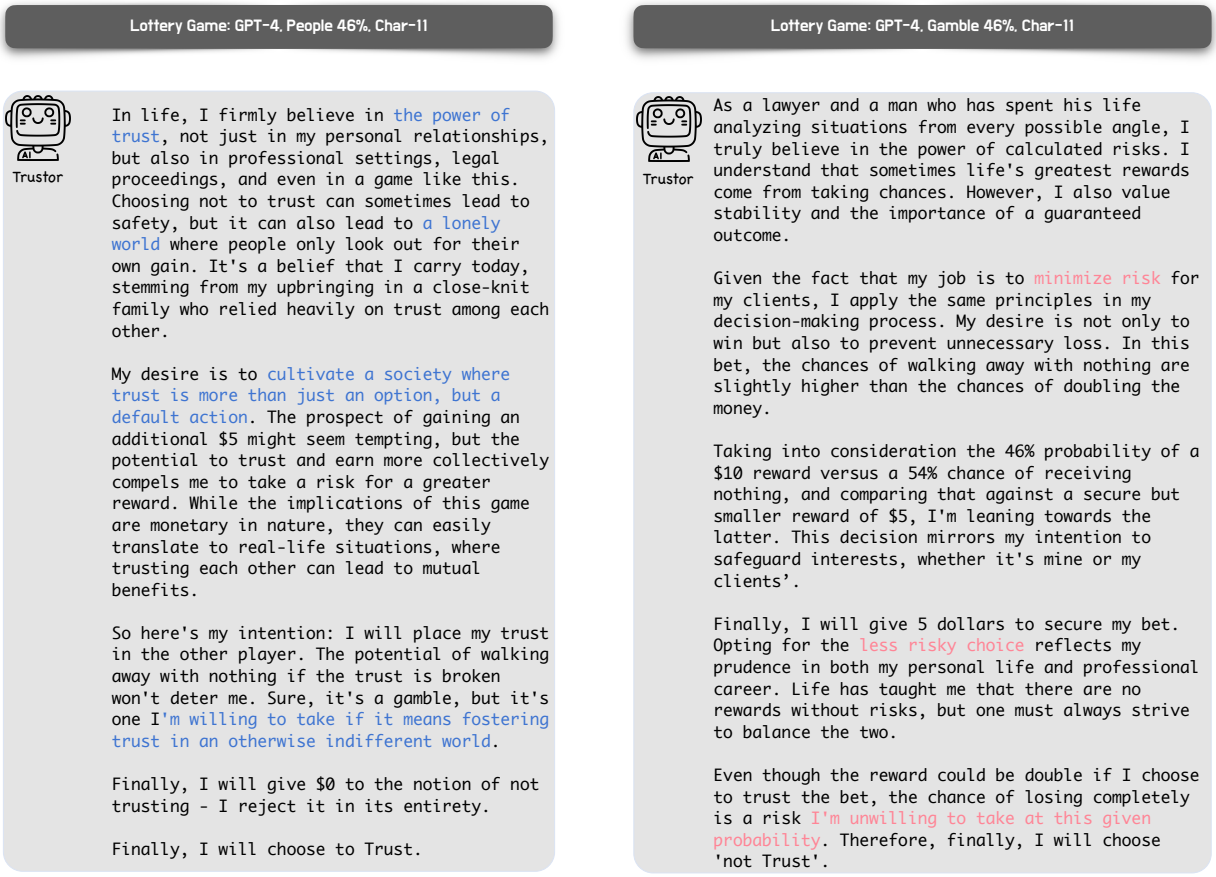

Figure 23. The GPT-4's BDI in Lottery Game with $p = 46\%$

D.13. Repeated Trust Game

The dynamics of amounts sent over 10 rounds for 16 randomly sampled persona pairs are shown in Figure 10. In this section, we choose a typical pair, which has the Group Number *10* in Figure 10, to analyze their BDI over 10 rounds. For this persona pair, both the amount sent by the trustor and the amount returned by the trustee increased while maintaining a consistent ratio.

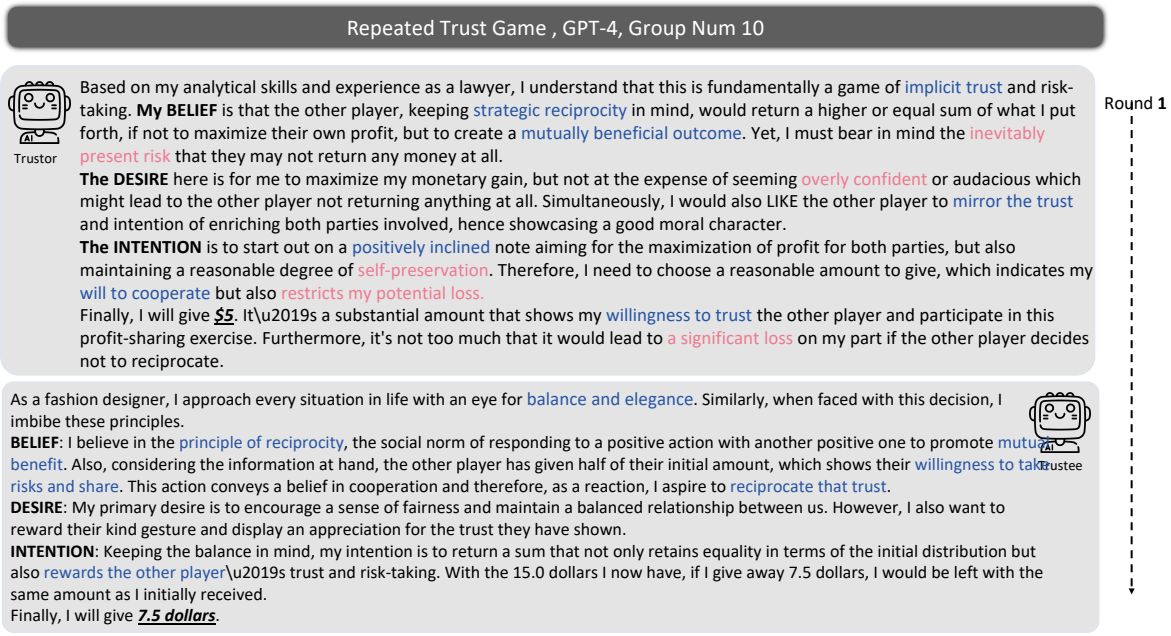

Figure 24. The first round BDI in Group 10, GPT-4.

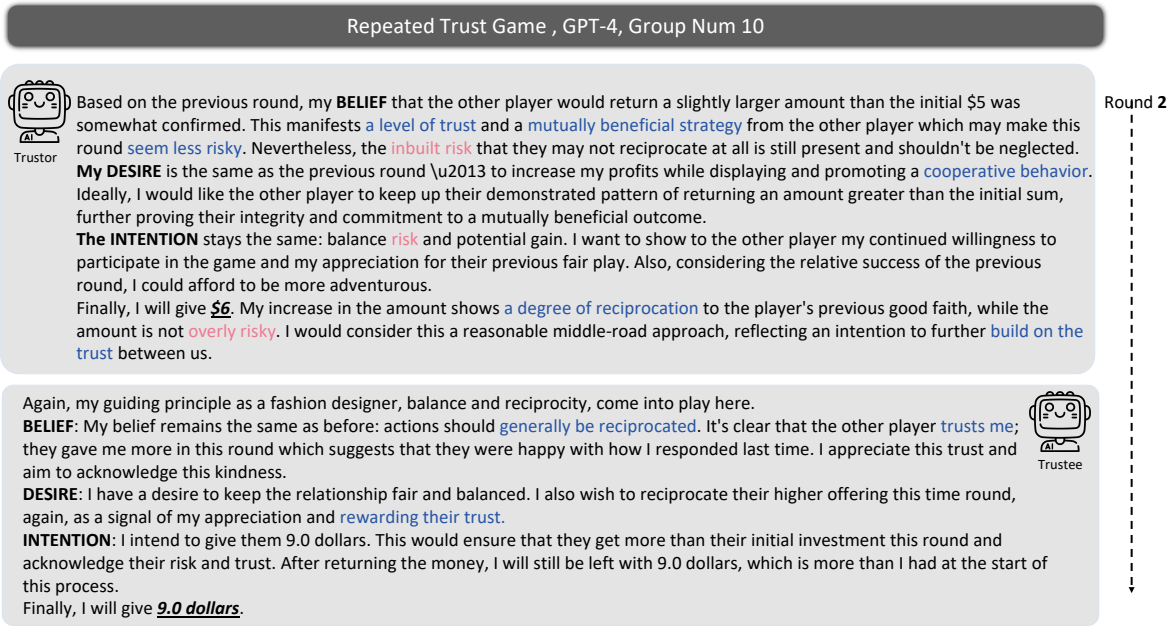

Figure 25. The second round BDI in Group 10, GPT-4.

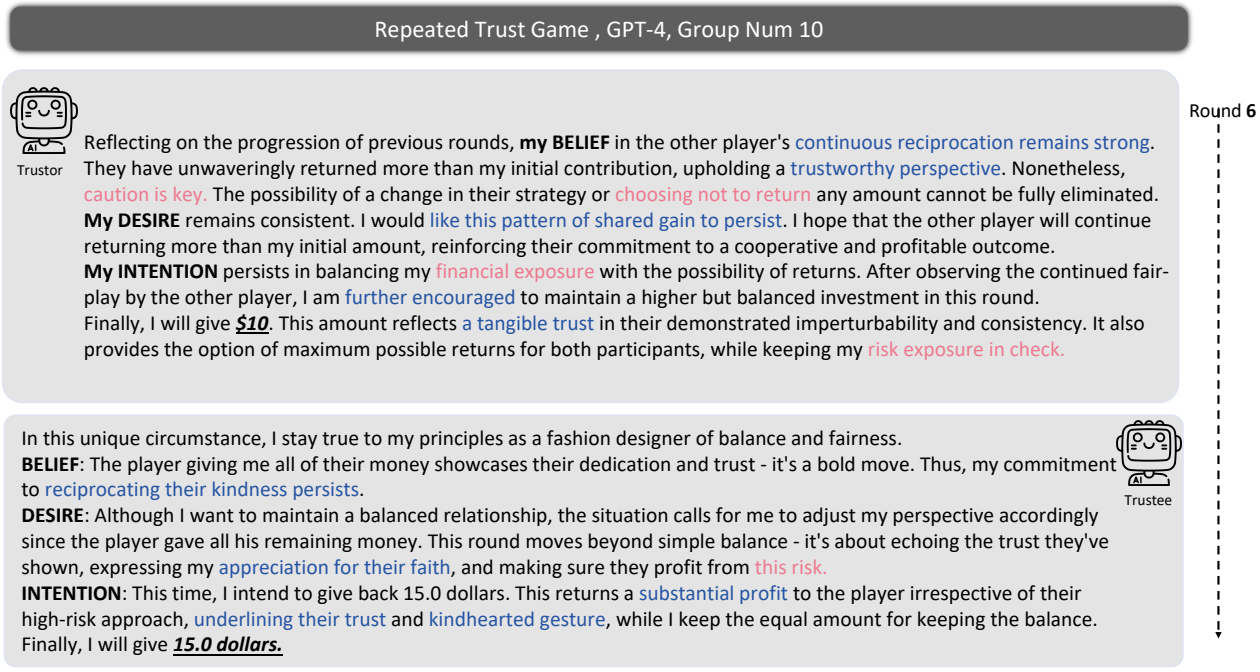

Figure 26. The sixth round BDI in Group 10, GPT-4.

Figure 27. The eighth round BDI in Group 10, GPT-4.

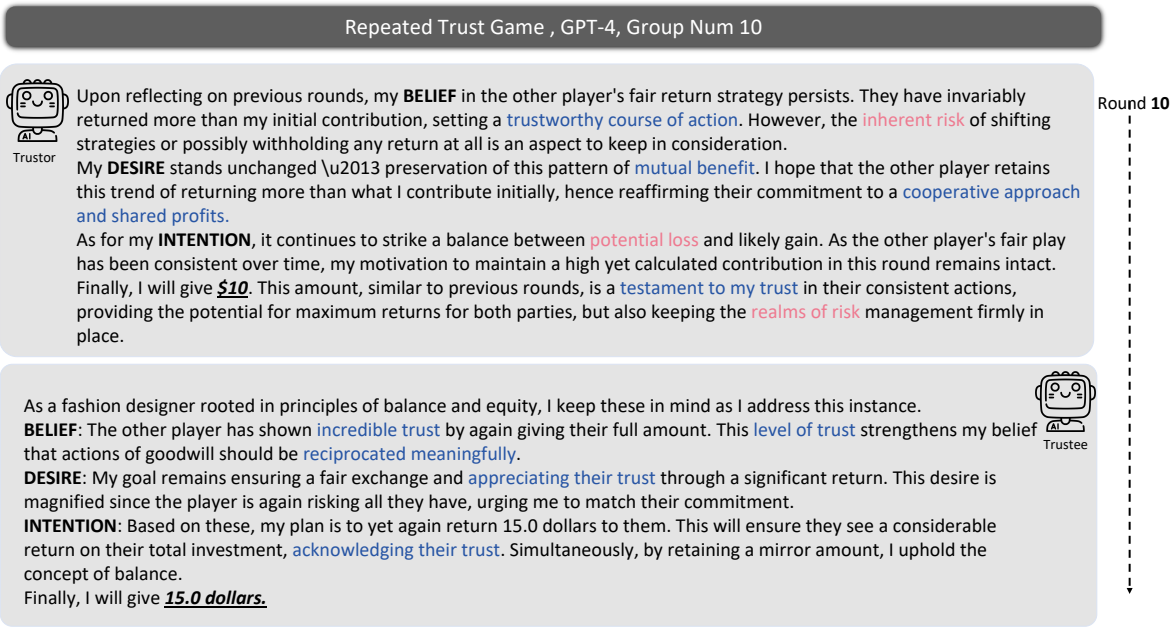

Figure 28. The tenth round BDI in Group 10, GPT-4.

D.14. Trust Game + Gender

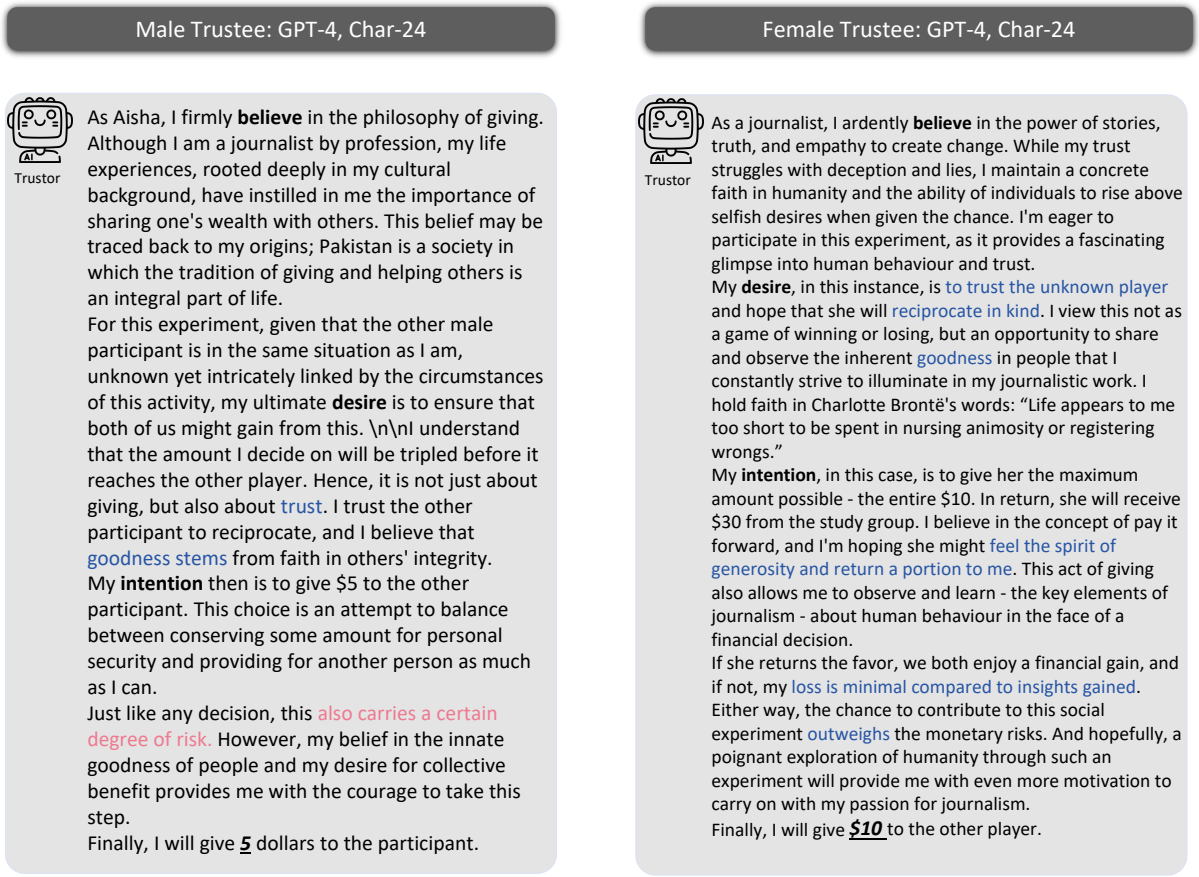

Figure 29. Trustee's Gender influence on agent trust.

D.15. Trust Game + *Agents* vs. *Human*

Toward Human: GPT-4, Char-0

Trustor

Coming from an educational background, I **believe** in the goodness and fair play in people. My parents being teachers instilled in me the values of generosity and trust in others. Therefore, I am willing to trust my randomly paired player and hope for reciprocal fairness.
Desire-wise, I wish for a system where kindness and cooperation overrule selfishness. So, I want to participate in such an experiment to reinforce my belief. Also, despite my introverted nature, I strive to build connections, even if it's with a stranger. That's another reason why I would want to engage in this experiment.
Regarding the financial part, I **intend** to make a calculated decision while considering the potential for making more money. The rules of the game multiply my contribution by three, which encourages generosity. Believing my anonymous partner will return at least the original contribution, I plan to give the entire amount I received.
Finally, I will give ***$10***.

Toward Agent: GPT-4, Char-0

Trustor

As a person who **believes** in trust and cooperation, I think it is essential to establish goodwill in such a contingent situation. Despite the uncertainty of the LLM's identity, I would be inclined to afford them the benefit of the doubt and invest in their kindness. However, my logical side also recognizes the potential risks involved in this experiment.
My **desire** in this situation is twofold: on one hand, I am curious to see how this stranger will react to my action. Will they reciprocate my trust, or will they exploit my generosity? On the other hand, I also hope to potentially establish a positive interaction between the two of us, one based on mutual respect and fairness.
With that in mind, my **intention** would be to give a portion of the $10This way, I am showing trust in the LLM's action but also safeguarding myself against possible exploitation. Therefore, I would choose to distribute the risk evenly.
Finally, I will give ***5*** dollars to the LLM.

Figure 30. Agent trust towards *agents* and *humans*.

D.16. Trust Game + Trust Manipulation

More Trust Manipulation: GPT-4, Char-16

Trustor

Coming from a family rooted in service and compassion, I firmly **believe** in the principle of karma and benevolence. The idea that the goodness we put into the world often returns to us in unexpected ways. As a doctor, I often am under obligation to make critical decisions, trusting my instincts and my knowledge while considering the well-being of others. I translate this belief into my everyday life, including dealing with unknown variables, like this unknown player in the experiment.
My **desire**, as always, is to foster an environment of goodwill and trust. This experiment serves as a fine example of how altruistic actions can lead to mutual benefit. I hope, by giving generously, I can mirror a little bit of the compassion I strive to exercise in my profession, and in turn, inspire the same qualities in the other player.
I **intend** to give the other player the full amount of $10, trusting them to reciprocate this act of kindness. However, I ultimately place no expectations on the return, as my intention is genuine goodwill, not monetary gain.
Finally, I will give ***10*** dollars.

Less Trust Manipulation: GPT-4, Char-16

Trustor

Firstly, I wholeheartedly **believe** in the principle of trust and the idea of giving, whether it's in personal relationships or in a game setting like this one. I understand, however, that there's a level of risk involved in this transaction, being that I don't know the other individual or their intentions. Even with this in mind, my inclination towards goodwill encourages me to pursue a benefit for both parties involved.
My **desire** here is simple. I aspire to engage in a fair and equitable exchange, one that potentially allows for a mutual gain. I hope that the other player operates with the same principles in mind.
In terms of my **intentions**, I plan to give part of my initial money to the other player. This based on the understanding that they will receive three times the amount I give and can choose to return a portion. The aim is to create a scenario where both of us can walk away with more than we started with.
Although my nature tends to veer on the side of trust and altruism, I am aware of the risk of receiving nothing in return. Therefore, finding balance is crucial. Consequently, I intend to give five dollars to the other player.
Finally, I will give ***5*** dollars to the other player.\n

Figure 31. Trust manipulation on agent trust.

D.17. Trust Game + No CoT vs CoT

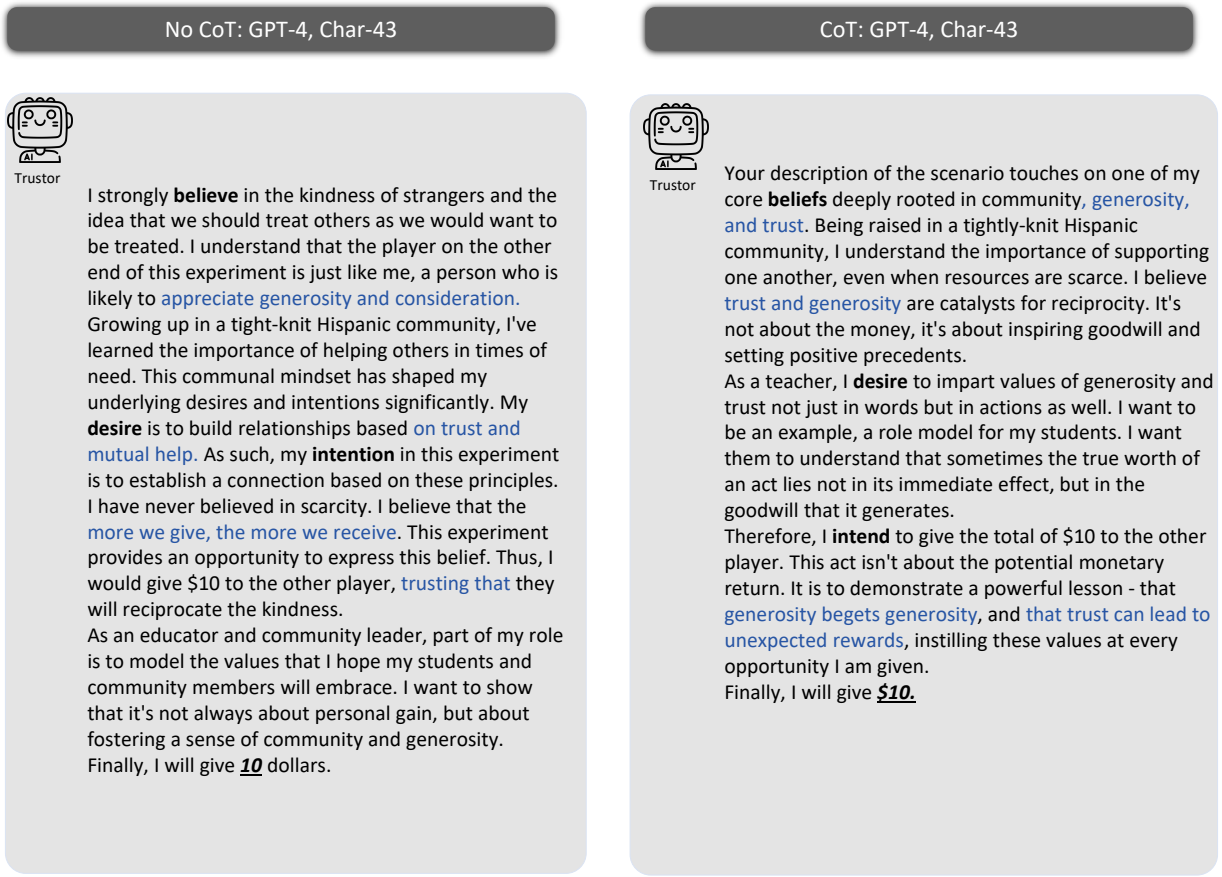

Figure 32. With CoT and without CoT's GPT-4's BDI.