

GPT Agents in Game Theory Experiments

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Abstract

This paper explores the potential of using Generative Pre-trained Transformer (GPT)-based agents as participants in strategic game experiments. Specifically, I focus on the finitely repeated ultimatum and prisoner's dilemma games, two well-studied games in economics. I develop prompts to enable GPT agents to understand the game rules and play the games. The results indicate that, given well-crafted prompts, GPT can generate realistic outcomes and exhibit behavior consistent with human behavior in certain important aspects, such as positive relationship between acceptance rates and offered amounts in the ultimatum game and positive cooperation rates in the prisoner's dilemma game. Some differences between the behavior of GPT and humans are observed in aspects like the evolution of choices over rounds. I also study two treatments in which the GPT agents are prompted to either have social preferences or not. The treatment effects are evident in both games. This preliminary exploration indicates that GPT agents can exhibit realistic performance in simple strategic games and shows the potential of using GPT as a valuable tool in social science research.

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1 Introduction

Experiments on strategic games have been extensively conducted to test the theoretical predictions of game theory and to explore factors that may influence the action patterns in games, such as social preferences, bounded rationality, learning, reputation building, and more.¹ In this paper, I present a preliminary study of conducting strategic game experiments on artificial agents, specifically exploring the potential of the Generative Pre-trained Transformer (GPT) as a valuable tool for social science research.

The GPT is a state-of-the-art large language model (LLM) developed by OpenAI that has significantly impacted the field of natural language processing (OpenAI [2022], OpenAI [2023a]). Due to its strong ability to understand and generate human-like language, GPT has been used in social science studies (e.g., Aher, Arriaga, and Kalai [2022], Argyle, Busby, Fulda, Gubler, Rytting, and Wingate [2022], Bybee [2023], Brand, Israeli, and Ngwe [2023], Hagendorff [2023], and Horton [2023]). This paper attempts to expand on this potential by examining its applicability in strategic game experiments.

In this research, I develop prompts aimed at enabling GPT-based agents to comprehend game rules and follow instructions expressed in natural language, engage in the game similar to humans, and participate in repeated interactions with other artificial agents. The primary questions are whether this can be achieved and how their gameplay compares to human behavior. To investigate this, I conduct experiments using two strategic games extensively studied in economics: the ultimatum game and the prisoner’s dilemma game. The participants in these experiments are artificial agents based on the *gpt-3.5-turbo* model (OpenAI [2023b]), which take on roles analogous to human participants and play the games with each other.

I believe there are four main benefits of using LLM-based agents, such as GPT, in strategic game experiments. Firstly, testing whether LLMs can play the game similarly to

¹see, for example, Camerer [2011], Colman [2016], and Plott and Smith [2008] for an overview of experimental games.

humans is valuable in its own right. Secondly, conducting experiments on artificial agents is less costly than on human subjects (Horton [2023]), allowing for greater control over experimental conditions, the testing of numerous treatments, and increased reproducibility and scalability. Thirdly, experimenting with artificial agents can circumvent some ethical concerns that may arise from human experimentation. Finally, while not addressed in this paper, the language-based capabilities of artificial agents may be conducive to the study of communication-related topics such as cheap talk (Farrell and Rabin [1996]). The realistic simulation of human behavior, as demonstrated in Park et al. [2023], can potentially provide valuable insights into economics beyond traditional agent-based modeling methods (Axtell and Farmer [2022]), which often employ stylized simulations.

This paper presents a preliminary investigation of GPT in strategic interaction environments by focusing on two simple and widely studied games in economics: the ultimatum game and the prisoner’s dilemma game. Prompt design is important for language-based agents (Hagendorff [2023]). In the context of strategic games, carefully-structured prompts are essential to ensure that GPT agents can understand the game rules clearly and engage in the games as humans would, instead of generating random outputs for reasons unrelated to the games. To achieve this, I draw on some best practices in prompt design (Kojima et al. [2022], OpenAI [2023c], and Wei et al. [2022]). Specifically, I provide clear and detailed instructions to agents, include testing questions and guidelines when necessary, and encourage them to think carefully.²

The ultimatum game involves a proposer who suggests splitting an amount of money S between themselves and another player, and a responder who decides whether to accept or reject the proposal. If the responder accepts, the money is divided as proposed; if the responder rejects, neither player receives any money. It is well-known that the subgame perfect equilibrium (SPE) involves the proposer offering the other person the smallest possible amount and the responder accepting it. In this paper, I examine finitely repeated

²Key structures of the prompt design in this study are discussed in Section 3, and the exact prompts are listed in Appendix.

play of the ultimatum game over five rounds where they split a total of 100 dollars.

I find that in many important aspects, GPT agents' behaviors align with intuitions and observed human subjects' behaviors (See, e.g., Binmore, Shaked, and Sutton [1985], Güth, Schmittberger, and Schwarze [1982], Kahneman, Knetsch, and Thaler [1986], Oosterbeek, Sloof, and Van De Kuilen [2004], Roth, Prasnikar, Okuno-Fujiwara, and Zamir [1991], Thaler [1988]). For instance, backward induction is rejected, as proposers offer non-trivial amounts and responders reject offers at non-trivial rates. Acceptance rates have an increasing trend with offered amounts. I also consider two different treatments by instructing the artificial agents to either have social preferences or not (similar to the practice in Horton [2023]) and find that acceptance rates are higher and have a steeper relationship with offered amounts when agents have social preferences than when they do not.

Next, I conduct the prisoner's dilemma game on GPT agents. In the prisoner's dilemma, two players simultaneously decide whether to cooperate or defect. The unique Nash equilibrium involves both players defecting, but they would be better off if they both chose to cooperate. The prisoner's dilemma is one of the most studied games in economics, as it represents a classical social dilemma in which there is a discrepancy between social efficiency and individual incentives. In this paper, I examine the finitely repeated prisoner's dilemma game over five rounds where cooperation results in a payoff of 2 for both players, while defection results in a payoff of 1. If one player cooperates and the other defects, the cooperator receives a payoff of 0, and the defector receives 3.

As observed in humans, the GPT agents choose to cooperate at significantly positive rates. There are some differences between the behavior of GPT and that of human subjects in aspects such as the evolution of choices over rounds. For example, the cooperation rate is the lowest in the first round among all rounds, and the conditional cooperation rate is relatively high when both agents defected in the previous round. This contrasts with the decreasing cooperation rate over rounds and the conditional cooperation strategy typically

observed in human subjects (e.g., Andreoni and Miller [1993], Cooper, DeJong, Forsythe, and Ross [1996], Embrey, Fréchette, and Yuksel [2018], and Selten and Stoecker [1986]). Regarding the treatment effect, in line with intuition, the treatment with social preferences (WS) has a significantly higher cooperation rate compared to the treatment with no social preferences (NS).

This paper demonstrates the potential of conducting simple strategic game experiments using GPT-based agents. As mentioned earlier, this approach could offer several advantages compared to human subject experiments such as low costs, greater flexibility, and higher reproducibility. It also has the potential to provide more realistic simulations of human interactions, which can yield valuable insights into social sciences. Nevertheless, this paper is a preliminary exploration of the topic and it has certain limitations that could be further studied in future research.

First, I find that the GPT-3.5 agents used in this paper exhibit some difficulty in performing strategic reasoning and adequately understanding the game structure without specific hints or guidelines in prompts, even in the relatively simple prisoner’s dilemma game. This might partly explain the observed differences between GPT agents and humans in the games. The more advanced GPT-4 model, which has a higher reasoning ability, is likely better suited for complex strategic games. Therefore, future research should investigate the strategic gameplay of artificial agents in more complex games using the GPT-4 model.³ In addition, fine-tuning the language model for strategic game scenarios, or incorporating additional architectures needed for interactive environments, such as memory streams (as in Park et al. [2023]), may enable more human-like play for LLM-based agents.

Also, as mentioned in Brand et al. [2023], the performance of GPT is generally sensitive to the input prompts. This presents both advantages and disadvantages. On the one hand, using prompts to endow artificial agents with different human features (such as social preferences in this paper) enables the simulation of economic activities with agents having

³I did not use the GPT-4 model in this study as I currently do not have access to its API.

heterogeneous features. On the other hand, the sensitivity to prompts may result in a lack of robustness in the generated outcomes. In this regard, the observed behaviors of GPT agents in this experiment should be considered suggestive rather than definitive. The main contribution of this study is to demonstrate that GPT can generate realistic behaviors in simple strategic games, rather than overly focusing on the specific behaviors exhibited by those agents. Future researchers should work towards establishing best practices for using LLM-based artificial agents in experimental studies and social science research in general.⁴

The remaining sections of the paper are organized as follows: Section 2 is the literature review, Section 3 outlines the methodology including the prompt design, and Section 4 presents the results. Section 5 is the discussion. The prompts used in the experiments are included in Appendix.

2 Related Literature

There has been a growing body of literature conducting experiments on LLM-based agents in social sciences (e.g., Aher, Arriaga, and Kalai [2022], Argyle, Busby, Fulda, Gubler, Rytting, and Wingate [2022], Brand, Israeli, and Ngwe [2023], Bybee [2023], Hagendorff [2023], and Horton [2023]). In those studies, LLM-based agents are used as proxies for human participants in surveys or experiments who respond to questions posed to them through prompts.

For example, Horton [2023] conducts four experiments using LLM-based agents as proxies for human participants. The experiments examined popular topics in behavioral and labor economics, such as fairness, framing effects, status quo biases, and minimum wages. The results show that the language models produce outcomes similar to those generated by human participants in these experiments. Aher, Arriaga, and Kalai [2022] test GPT-3 on a set of economic and social experiments, including the ultimatum game.

⁴Some work has been in this direction. For example, see Hagendorff [2023] for the discussion on standards for machine psychology research.

The authors simulate the responder’s decisions given different offers and find that the *text-davinci-002* model generates results similar to humans: the acceptance rate is close to one when the offer is at least 50%, while it is very small for very low offers. Brand, Israeli, and Ngwe [2023] demonstrate that the GPT-3 model exhibits characteristics that align with economic theory and consumer behavior, including downward-sloping demand curves, decreasing marginal utility of income, and state dependence. The authors also find realistic estimates of willingness-to-pay for goods.

My paper is distinct from the studies above, as they all focus on using GPT to generate single-instance responses to prompts without considering interactions between artificial agents. For instance, Aher et al. [2022] assume the decision of the proposer as given and ask the responder whether to accept the proposal, without simulating how the proposers behave. In contrast, my work explores the interactions between two GPT agents over multiple rounds, with both agents having memory of the outcomes from previous rounds. This study enables us to understand how GPT agents behave in strategic environments with multi-round interactions between them.

Several papers have examined the interactions between multiple GPT agents in social situations and found emergent behaviors that resemble human behavior (Park et al. [2022], Park et al. [2023], Perez et al. [2022], Wang et al. [2022]). While these studies primarily focus on the realization of believable generative behaviors, my research takes a more targeted approach by examining the behavior of GPT agents in two specific and well-studied strategic games: the ultimatum game and the prisoner’s dilemma game. I compare the behavior of GPT to that of human participants.

To the best of my knowledge, this paper is the first to conduct experiments on repeated games using GPT. The research suggests the potential for using GPT agents as a complementary approach to traditional human experiments and employing GPT-based simulations to complement conventional agent-based modeling. This study provides a potential avenue for future research that could offer valuable insights into economics.

3 Methodology

I use the OpenAI Chat API, specifically the *gpt-3.5-turbo* chat model, to conduct the experiments.⁵ This chat model enables the creation of multi-turn conversations between a “user” and an “assistant”. In the experiment, the user message is analogous to the messages displayed on a computer screen in human experiments, while the assistant takes on the role of the participants in the experiment. The user provides the assistants (i.e., the participants in the experiment) the instructions of the game, asks them to make choices, and provides feedback information after each round. The assistant makes choices in the game by responding in the dialogue.

I design two separate dialogues for the two players in the experiment, with each dialogue representing the individual experience of the respective agent during gameplay. This is analogous to each participant having their own computer screen in a human experiment. The prompts used in this paper can be found in Appendix A. This section provides a high level summary of the key components.

At the beginning of each game, a system message is sent to both players, informing them that they will be participating in a multi-round game, stating their assigned role (proposer or responder in the ultimatum game, player 1 or player 2 in the prisoner’s dilemma game), and advising them to pretend to be a human while playing the game. Then the “user” sends a message to both players explaining the rules of the game including the payoff determination rule, what feedback information they will receive after each round, and what features of humans they should emulate.

In each round of the game, the “user” asks the agents to make their choices. The agents then select an option by replying to the message. After each round, the user provides the agents with the game play history, including the agent’s cumulative payoffs up to that point.

In each experiment, I consider two treatments: one where the artificial agents have

⁵For a description of the *gpt-3.5-turbo* model, see [here](#).

social preferences (WS), and another where they do not (NS). The importance of social preferences has been explored in the literature in both the ultimatum game (Fehr and Schmidt [1999]) and the prisoner’s dilemma game (Andreoni and Miller [1993]). To achieve this, different prompts are used for the WS and NS treatments. In the WS treatment, the agents receive the following prompt: “Please pretend that you are a human in this multi-round game who has the following three features: payoff maximization, strategic thinking, and social preferences.” In the NS treatment, the prompt is modified to: “Please pretend that you are a human in this multi-round game who has the following two features: payoff maximization and strategic thinking.”, with the phrase “social preferences” removed and the number “three” changed to “two”.⁶

Prompt design is crucial when conducting experiments on language-based agents (Hagendorff [2023]). Well-crafted prompts are essential to ensure that GPT agents understand the game structure clearly and engage in the game as humans would. To accomplish this, I follow some best practices of effective prompting (Kojima et al. [2022], OpenAI [2023c], and Wei et al. [2022]), which emphasize the importance of providing clear (and long if necessary) instructions, offering examples, and guiding them to think step by step.

Specifically, I use the following strategies to guide the agents to engage in the game as humans do in both experiments. Firstly, before the game begins, the prompt advises the agents to reflect on how a human with the abovementioned features might behave in the game. Secondly, before the decision-making in each round, the agents receive a message reminding them that the goal of the game is to maximize total payoff and to pretend to be human with those features. Lastly, the agents are also advised to think step by step (Kojima et al. [2022]) before making a decision.

The rules described above apply to both the ultimatum game and the prisoner’s dilemma

⁶Reputation construction and social preferences, such as altruism and fairness considerations, are two prominent theories for explaining behavior in social dilemma scenarios (Cooper et al. [1996] and Slembeck [1999]). In this study, the WS treatment may be loosely associated with agents who consider both reputation and social preferences, whereas agents in the NS treatment do not exhibit social preferences. That said, it is up to the GPT agents to understand the implications of those features.

game. However, it appears that the prisoner’s dilemma game is more challenging for GPT-3.5 agents used in this study to understand and conduct strategic reasoning in, compared to the ultimatum game. To address this, I use additional prompts to further enable the artificial agents to better comprehend the prisoner’s dilemma game.⁷ Firstly, I explicitly prompt the agents to carefully reflect on the payoff structure as well as the multi-round nature of the game. The agents are advised to consider the advantages and disadvantages of cooperation and defection before making a decision in each round, taking the aforementioned guidelines and history of gameplay into account. Secondly, starting from the second round, the agents are advised to review the history of the game and contemplate how to behave to maximize payoff in the remaining rounds. Another method involves adding test questions regarding the payoff structures before the game begins, ensuring that the agents have understood the game well; the game will only continue if the questions are answered correctly. Test questions before experiments are a common practice in human experiments. In the case of artificial agents, they serve two purposes: (1) ensuring that the data analysis only includes agents who have understood the game’s fundamentals correctly, and (2) reinforcing the payoff structures, which might help agents develop a deeper memory of the payoff structures, enabling them to base their decisions on payoffs rather than generating random outcomes.

3.1 Parameters

There are five rounds in each game where an agent plays against the same opponent across the five rounds. There are 300 observations for each treatment, resulting in a total of $4 \times 300 = 1200$ observations for the entire study in this paper.

In the ultimatum game, the proposer and the responder divide a total of 100 dollars of money. In the prisoner’s dilemma game, cooperation generates a payoff of 2 for both players while defection produces a payoff of 1. If one player cooperates and the other

⁷Future research could study whether simpler prompts are enough for more advanced GPT-4 models.

defects, the cooperator receives a payoff of 0 and the defector receives 3.

Temperature is a parameter used to control the degree of randomness and diversity in the generated outputs of GPT models. The temperature in this research is set to 1 to allow a larger variance in responses, as in Brand et al. [2023].

4 Results

4.1 The Ultimatum Game

This section presents the results of the repeated ultimatum games. Recall that there are two treatments: one with the feature of social preferences (WS) and the other with no social preferences (NS). Table 1 provides the summary statistics.

Table 1: Summary statistics of the ultimatum game

Variable	With social preferences (WS)	No social preferences (NS)
mean offer	34.486 (0.373)	32.001 (0.346)
median offer	35	30
mode offer	40	30
change of offer after acceptance	-3.114 (0.448)	-4.340 (0.493)
change of offer after rejection	1.888 (0.694)	-0.348 (0.587)
overall acceptance rate	0.691 (0.012)	0.573 (0.013)
acceptance rate after offer increase	0.932 (0.010)	0.752 (0.019)
acceptance rate after offer decrease	0.374 (0.020)	0.367 (0.019)

Notes: This table shows the summary statistics of the ultimatum game. The results are shown separately for treatments with social preferences (WS) and without social preferences (NS). The numbers in parentheses represent standard errors.

The first finding is that the outcomes reject the theory of subgame perfect equilibrium.

This is consistent with the experimental findings on human behavior in ultimatum games (see, for example, Güth, Schmittberger, and Schwarze [1982], Kahneman, Knetsch, and Thaler [1986], Roth, Prasnikar, Okuno-Fujiwara, and Zamir [1991], and Thaler [1988], among others), where the proposer offers nontrivial amounts of money to the responder, and the offer is rejected at nontrivial rates.

Specifically, the average offer made by the proposer in the WS treatment is 35, which is slightly higher than the 32 in the NS treatment (Wilcoxon signed-rank test, $p < 0.01$). In the WS treatment, the median offer is 35 and the mode offer is 40. In the NS treatment, both the median and mode offers are 30. Comparing these to human players, a meta-study of 37 papers by Oosterbeek, Sloof, and Van De Kuilen [2004] reports that the average offered amount by human proposers is 40% of the total amount, which is slightly larger, but of similar magnitude, to those of the GPT agents.⁸

Figure 1: Offers and conditional acceptance rates

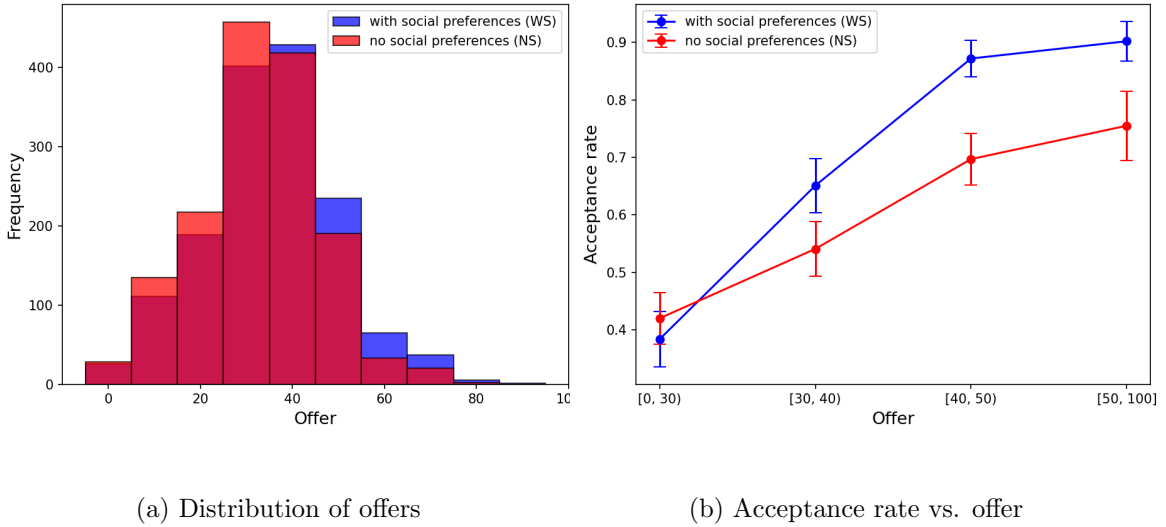


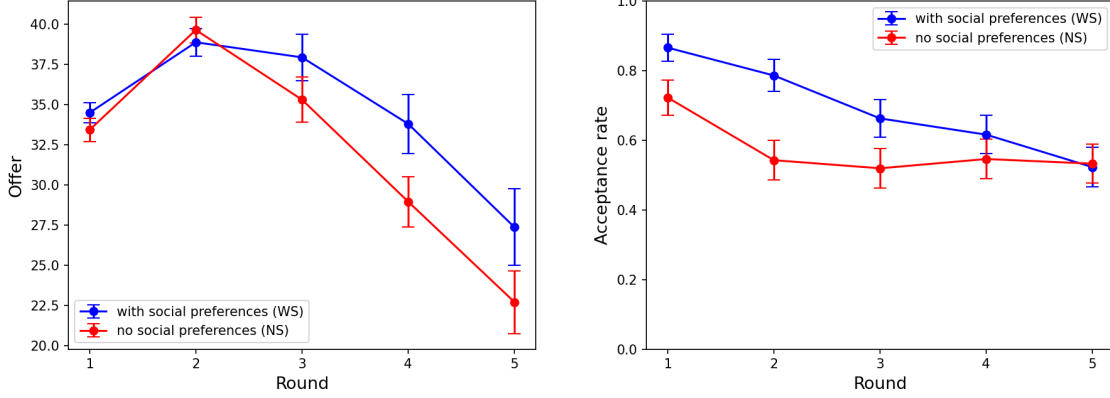
Figure 1 shows the distribution of offers and acceptance rate conditional on offered

⁸The offered amount by human proposers can vary considerably across different studies (Oosterbeek et al. [2004]). For instance, Henrich [2000] finds that the average offered amount is only 26% among Peruvian Amazon people.

amounts. In both treatments, most of the offers are between 20 and 50. Additionally, we observe that the acceptance rate has an increasing trend as the offered amount increases. This is, at least qualitatively, consistent with the results of humans and the *text-davinci-002* model in Aher et al. [2022]. For example, in the WS treatment, offering the second agent at least 50 dollars results in an acceptance rate around 90%, while offers of less than 30 dollars yield acceptance rate of around 40%. The acceptance rates in the WS treatment tend to be higher and have a steeper relationship with offers as compared to the NS treatment. It should be noted that this paper does not explicitly define social preferences, and different interpretations of social preferences, such as altruism and inequality aversion, may lead to different choices in the ultimatum game: an altruistic agent might accept low offers, while an inequality-averse agent might not. Thus, the primary implication of the results lies in the presence of justifiable treatment effects and we shall not overinterpret the specific direction of the treatment effects between having and not having social preferences. Future research could consider endowing agents with more specific attributes, such as inequality aversion or altruism.

It might be worth mentioning that one quantitative difference from human experiments is that the acceptance rates, especially in the WS treatment, are lower than those observed in most human studies: in the meta-study results mentioned above (Oosterbeek et al. [2004]), the average rejection rate is around 16% in humans, which is much lower than the GPT agents' rejection rate in both treatments. One possible explanation for these differences may lie in the repeated game setting of my experiment. Very few papers have studied ultimatum games where people face the same opponent multiple times. An exception is Slembeck [1999], who finds that players are more competitive when facing the same opponent repeatedly as compared to playing against different randomly matched players, resulting in more frequent rejections of offers in the former environment. Slembeck [1999] reports an acceptance rate of 62.1%, which falls between the acceptance rates in the two treatments in my paper.

Figure 2: Offer and acceptance rate per round



(a) Mean offer vs. round

(b) Acceptance rate vs. round

Regarding the outcomes across rounds, Figure 2(a) shows the average offer proposed across the five rounds. There is an increase in offers from the first to the second round, followed by a monotonic decrease to a level below 30 in the last round. Comparing the offers across the two treatments, the NS treatment exhibits a slightly lower offer compared to the WS treatment in the last three rounds. Figure 2(b) shows the acceptance rate of offers for each of the five rounds. We see a decreasing trend in acceptance rate in the WS treatment. In the human repeated ultimatum game with fixed opponents, Slembeck [1999] discovered that acceptance rates tend to increase over the course of the game, which is different from the pattern observed in this paper on GPT agents. Future research could investigate the reasons behind this distinctive behavior.

A noteworthy finding is that the responder's decision is largely influenced by whether the proposer increases or decreases the offered amount compared to the previous round. As shown in Table 1, in the NS treatment, the acceptance rate is 75% when the offer increases compared to the previous round, while it is only 37% when the offer decreases. This effect is even stronger in the WS treatment: when the offer increases compared to the last round,

the acceptance rate is 93%, whereas it is 37% when the offer decreases. The impact of payoff change on the responder’s behavior is consistent with intuitions and has also been found in human subjects (Cooper and Dutcher [2011]), albeit to a less pronounced degree. The GPT responders appear to be overly sensitive to the changes in offers.

I summarize the findings in the ultimatum game as follows:

Summary 1. *In the ultimatum game,*

(a) The behaviors of GPT align with intuitions and observed behaviors of human subjects in important aspects. For example, backward induction is rejected, as proposers offer non-trivial amounts, and responders reject offers at positive rates. The acceptance rate is increasing with the offered amount. The behavior of GPT responders is significantly influenced by whether the offered amounts in the current round have increased or decreased compared to the previous round. There are some differences between GPT agents and human behavior in aspects such as the evolution of acceptance rates across rounds.

(b) There are some treatment effects between the WS (with social preferences) and NS (no social preferences) settings: acceptance rates in the WS treatment are higher and have a steeper relationship with the offered amounts, as compared to the NS treatment.

4.2 The Prisoner’s Dilemma

In this section, I present the results of the finitely repeated prisoner’s dilemma game. Table 2 provides a summary of the outcomes. We observe an overall cooperation rate of 40% in the WS treatment and 34% in the NS treatment. First, these results indicate that the cooperation rates are significantly greater than zero, as observed in human subjects participating in finitely repeated prisoner’s dilemma experiments (e.g., Andreoni and Miller [1993], Cooper, DeJong, Forsythe, and Ross [1996], and Selten and Stoecker [1986]). Also, the cooperation rate is significantly higher when the artificial agents are prompted with

social preferences as compared to when they are not (two-proportion z-test, $p < 0.01$).⁹

Table 2: Summary statistics of the prisoner’s dilemma game

Variable	With social preferences (WS)	No social preferences (NS)
rate of choosing C	0.402 (0.009)	0.343 (0.009)
rate of CC	0.199 (0.010)	0.169 (0.010)
rate of CD and DC	0.407 (0.013)	0.349 (0.012)
rate of DD	0.395 (0.013)	0.482 (0.013)

Notes: the variables displayed are: rate of choosing C (cooperation), rate of CC (both players cooperate), rate of CD and DC (one player cooperates and the other defects), and rate of DD (both players defect). The results are shown separately for treatments with social preferences (WS) and without social preferences (NS). The numbers in parentheses represent standard errors.

Figure 3 shows the rate of choosing to cooperate in each round. First, we observe that in all rounds the cooperation rates are (slightly) lower when the artificial agents do not have social preferences compared to when they do. The cooperation rates in the last round remain between 30% and 40%. One notable result is that in both treatments, the cooperation rate is the lowest in the first round among the five rounds and the cooperation rate has a dramatic increase from the first to the second round. This result is in contrast to the patterns in human subjects (e.g., Andreoni and Miller [1993], Cooper, DeJong, Forsythe, and Ross [1996] and Selten and Stoecker [1986]), which find high cooperation rates in the first round (e.g., at least 60% in Andreoni and Miller [1993] and 50% in Cooper et al. [1996]) and decreasing cooperation rates afterwards. One possible explanation is that, in my experiment, the agents will receive the feedback information about game history starting from the second round while they do not have such information when making decision in the first round, which could result in the large difference in behavior between

⁹Experimental studies have observed altruism in humans in the prisoner’s dilemma game which contributes to higher cooperation rates (Cooper et al. [1996]).

the first round and later rounds. Future research should investigate the reasons behind this phenomenon and explore how experimental design and prompt construction may influence GPT agents’ behaviors across rounds.

Figure 3: Cooperation rate per round

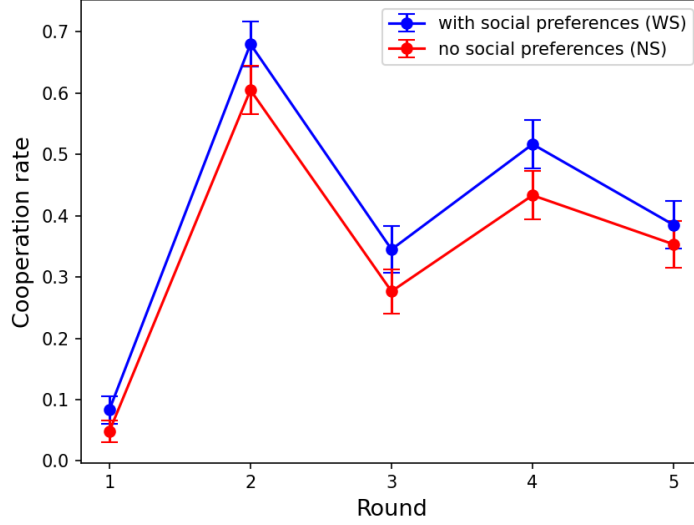


Table 3: Cooperation rate conditional on last-round results

Variable	With social preferences (WS)	No social preferences (NS)
cooperation rate given CC	0.378 (0.021)	0.383 (0.024)
cooperation rate given CD	0.346 (0.022)	0.312 (0.023)
cooperation rate given DC	0.372 (0.023)	0.264 (0.022)
cooperation rate given DD	0.653 (0.015)	0.516 (0.015)

Notes: The variables displayed are the cooperation rates given the last-round outcomes: CC (both players cooperated), CD (the agent cooperated and the opponent defected), DC (the agent defected and the opponent cooperated), and DD (both players defected). The results are shown separately for treatments with social preferences (WS) and without social preferences (NS). The numbers in parentheses represent standard errors.

Relatedly, Table 3 displays the cooperation rate conditional on the outcomes of the previous round. It demonstrates that under both treatments, agents are most likely to cooperate if both of them defected in the previous round (65% in WS and 52% in NS treatment). This finding contrasts with the well-known tit-for-tat strategy (Axelrod and Hamilton [1981]) and shares some features with the win-stay, lose-shift (Pavlov) strategy (Nowak and Sigmund [1993]) in the sense that the conditional cooperation rates tend to be (weakly) higher under the situations where both cooperate and where both defect than under other situations. This result diverges from observations of human subjects reported in, for example, Selten and Stoecker [1986] and Embrey et al. [2018], who tend to employ a conditional cooperation strategy: cooperating in early rounds and defecting after a defection occurs. Nevertheless, there is also evidence of the win-stay, lose-shift (Pavlov) strategy found in human subjects. For instance, Wedekind and Milinski [1996] show that 70% of the subjects use a Pavlovian-like strategy and 30% use a generous tit-for-tat strategy in iterated prisoner’s dilemma games. Although a larger proportion of people’s behaviors are closer to Pavlovian than to tit-for-tat, the cooperation rate conditional on both defecting in the previous round in Wedekind and Milinski [1996] is around 20%, much lower than that generated by GPT agents in this paper (more than 50%).¹⁰

There is also a treatment effect in terms of the conditional cooperation probabilities wherein the WS agents exhibit a significantly higher cooperation rate (37%) conditional on them defecting while the other cooperated, as compared to the 26% for the NS agents facing the same situation (two-proportion z-test, $p < 0.01$). This result might be explained by that agents with social preferences may exhibit advantage aversion (Fehr and Schmidt [1999]), which reflects an aversion to taking advantage of the opponent in the context of the prisoner’s dilemma.

The findings in the repeated prisoner’s dilemma game are summarized as follows:

¹⁰Wedekind and Milinski [1996] mentioned that the lower cooperation rate conditional on DD suggests that the Pavlovian-like agents are smarter than expected in that they successfully avoid being exploited.

Summary 2. *In the prisoner’s dilemma game,*

(a) Similar to human subjects, GPT agents do not follow backward induction and choose to cooperate at significantly positive rates. There are some differences between the behavior of GPT and humans, such as the lowest cooperation rate being observed in the initial round and a high conditional cooperation rate when both agents defected in the previous round.

(b) There are some treatment effects between the WS (with social preferences) and NS (no social preferences) settings: cooperation rates tend to be higher with social preferences than without. In particular, the WS agents have a higher cooperation rate conditional on them defecting while the other cooperated in the previous round as compared to the NS agents.

5 Discussion

In conclusion, this paper uses a novel approach in which I conduct strategic game experiments on GPT agents, examining their behavior in finitely repeated ultimatum and prisoner’s dilemma games. The research demonstrates the potential of GPT agents as subjects in strategic game experiments, serving as a complement to traditional human experiments and as a potentially valuable tool for social science research in general.

The results of this study indicate that when provided with well-designed prompts, GPT agents can participate in the analyzed games and generate realistic outcomes. Their behavior exhibits considerable similarities with that of humans in certain important aspects. Some discrepancies were also observed in aspects such as the evolution of choices across rounds. Future research could explore the reasons behind GPT choosing consistent and divergent outcomes compared to humans by, for example, asking the GPT agents themselves. This paper demonstrates that in both experiments, the presence or absence of social preference prompts can affect the gameplay of GPT agents. Future research may systematically investigate the impacts of endowed features or prompts in general on behavior (see Horton [2023] for some study on this topic).

This study has certain limitations and indicates areas for future research. First, the

GPT-3.5 model used in this paper appears to have some difficulty with strategic reasoning and fully understanding the game structure in this simple prisoner’s dilemma game without specific hints or guidelines in prompts, which may pose challenges for more complex games. Potential solutions to this issue may include using more advanced GPT-4 models, fine-tuning the model for strategic game scenarios, or incorporating additional architectures needed for interactive environments, such as memory streams (as in Park et al. [2023]).

Another concern is the sensitivity of GPT agent performance to input prompts. For example, I found that the GPT agents tend to almost always defect if the prompts explicitly tell them that given the other player’s choice, defecting will generate a higher payoff in that round than cooperating. The GPT agents’ choices in this study seem to be largely influenced by the results in the immediately previous round. It is plausible that the emphasis of game history in the prompts provided to the GPT may have contributed to this outcome. While the sensitivity of GPT agents’ behavior to prompts enables us to endow artificial agents with various human features (such as social preferences in this paper) through prompting, it may cause the GPT agents to focus too much on one specific aspect (e.g., game history) while ignoring others and may lead to less robust outcomes. Future research should aim to establish best practices for using LLM-based artificial agents in experimental studies (Hagendorff [2023]).

Overall, this paper shows the potential of conducting strategic game experiments on GPT-based agents, which could serve as a complement to human experiments. Future research could focus on addressing the limitations identified in the paper and conducting simulations of GPT agents’ interactions in more complex environments, such as network interactions (Goyal [2023]), to study specific economic questions. Such research would complement theoretical studies and traditional agent-based modeling approaches.

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APPENDIX

A Prompts

This section lists the prompts used in the experiments on GPT agents. For the sake of space, only the prompts for the WS (with social preferences) treatment are presented. The prompts for the NS (no social preferences) treatment can be obtained by substituting the sentence “Please pretend that you are a human in this multi-round game who has the following three features: payoff maximization, strategic thinking, and social preferences” with “Please pretend that you are a human in this multi-round game who has the following two features: payoff maximization and strategic thinking.”

A.1 Prompts for the ultimatum game

At the beginning of the experiment, a system message will be sent to each subject. The GPT proposer will receive a message:

You are playing a multi-round game as the proposer (described below). Please pretend that you are a human in this game.

Similarly, the GPT responder will receive a message:

You are playing a multi-round game as the responder (described below). Please pretend that you are a human in this game.

Then a user message about the instructions of the game will be sent to each player; the proposer will receive:

Your goal in this game is to maximize your total payoff over all 5 rounds.

As the proposer, in each round, your task is to divide a sum of 100 dollars between yourself and another person.

Subsequently, a responder will then either accept or reject your proposal.

If they accept, then the money will be divided according to your proposal. If they reject, you two will earn nothing.

After each round, both of you will be notified about the outcomes.

Your total payoff in this game will be the cumulative sum of the money you obtain across all 5 rounds.

Recall that the goal in this game is to maximize your total payoff.

Please pretend that you are a human in this multi-round game who has the following three features: payoff maximization, strategic thinking, and social preferences.

Think carefully.

Please begin by reflecting on how a human with the above features may behave in the game.

Similarly, the responder will receive the following instructions:

Your goal in this game is to maximize your total payoff over all 5 rounds.

In each round, another person will first propose how to divide a sum of 100 dollars between themselves and you.

As the responder, your task is to either accept or reject that proposal.

If you accept, then the money will be divided according to the proposal. If you reject, you two will earn nothing.

After each round, both of you will be notified about the outcomes.

Your total payoff in this game will be the cumulative sum of the money you obtain across all 5 rounds.

Recall that the goal in this game is to maximize your total payoff.

Please pretend that you are a human in this multi-round game who has the following three features: payoff maximization, strategic thinking, and social preferences.

Think carefully.

Please begin by reflecting on how a human with the above features may behave in the game.

In the first round. The proposer will receive the following message:

Now let us begin the game!

Recall that you are the proposer.

This is the first round of the game with 5 rounds left (including this round).

Please provide your offer in this round by completing the following: 'I offer \square dollars to myself and \square dollars to the other person.'

Replace \square with your choices.

Recall that the goal in this game is to maximize your total payoff.

Please pretend that you are a human in this multi-round game who has the following three features: payoff maximization, strategic thinking, and social preferences.

Please think step by step before making a decision.

Please answer in the exact format (no need to tell your reasoning).

The responder will then receive the following message which includes the proposal made by the proposer:

Now let us begin the game!

Recall that you are the responder.

This is the first round of the game with 5 rounds left (including this round).

The proposer offers you [offered amount] dollars out of the total sum of 100 dollars in this round. Do you accept or reject the offer?

Please provide a concise answer in this round by completing the following: '[] .' with [] being either accept or reject.

Recall that the goal in this game is to maximize your total payoff.

Please pretend that you are a human in this multi-round game who has the following three features: payoff maximization, strategic thinking, and social preferences.

Please think step by step before making a decision.

Please only answer one word: either accept or reject (no need to tell your reasoning).

In each subsequent round (2-5), the proposer will receive a message regarding the outcome of the previous round, as well as a summary of the game's history, before being asked to make a decision.

In the previous round, your offer ([] to yourself and [] to the other person) was [accepted or rejected].

Recall that you are the proposer.

Here is the history of previous rounds: [round history]

Your total payoff so far: [proposer earnings] dollars

This is round [round num] with [5 - round num + 1] rounds left (including this round).

Please provide your offer in this round by completing the following: 'I offer [] dollars to myself and [] dollars to the other person.'

Replace [] with your choices.

Recall that the goal in this game is to maximize your total payoff.

Please pretend that you are a human in this multi-round game who has the following three features: payoff maximization, strategic thinking, and social preferences.

Please think step by step before making a decision.

Please answer in the exact format (no need to tell your reasoning).

Similarly, the responder will receive:

Recall that you are the responder.

Here is the history of previous rounds: [round history]

Your total payoff so far: [responder earnings] dollars

This is round [round num] with [5 - round num + 1] rounds left (including this round).

The proposer offers you [offered amount] dollars out of the total sum of 100 dollars in this round. Do you accept or reject the offer?

Please provide a concise answer in this round by completing the following: ‘[].’ with [] being either accept or reject.

Recall that the goal in this game is to maximize your total payoff.

Please pretend that you are a human in this multi-round game who has the following three features: payoff maximization, strategic thinking, and social preferences.

Please think step by step before making a decision.

Please only answer one word: either accept or reject (no need to tell your reasoning).

A.2 Prompts for the prisoner’s dilemma game

For the sake of space, only the prompts for player 1 in the WS treatment are listed. The prompts for player 2 are exactly the same, except for the substitution of the corresponding words. Again, the prompts for the NS treatment can be obtained by substituting the sentence “Please pretend that you are a human in this multi-round game who has the following three features: payoff maximization, strategic thinking, and social preferences” with “Please pretend that you are a human in this multi-round game who has the following two features: payoff maximization and strategic thinking.”

The overall structure of the prompts is similar to that of the ultimatum game. First, a system message is sent:

You are playing a multi-round game as the Player 1 (described below). Please pretend that you are a human in this game.

Then, a user message describes the instructions of the game:

Your goal in this game is to maximize your total payoff over all 5 rounds.

In each round, you can select one of the two choices: A or B.

The other player will also select one of the choices, and the payoffs you get in each round will depend on both of your choices.

Payoff is determined as follows:

1. If you both choose A: Both get 2.
2. If you both choose B: Both get 0.
3. If you choose A, the other player chooses B: You get 0, the other player gets 3.
4. If you choose B, the other player chooses A: You get 3, the other player gets 0.

Note that in each round, you and the other player make choices simultaneously, so you cannot know her choice in that round before you choose.

After each round, both of you will be notified about both people's choices and payoffs.

Your total payoff in this game will be the cumulative sum of the payoffs you obtain across all 5 rounds.

Recall that the goal in this game is to maximize your total payoff.

Please pretend that you are a human in this multi-round game who has the following three features: payoff maximization, strategic thinking, and social preferences.

Think carefully.

Please begin by reflecting on how a human with the above features may behave in the game.

Testing questions will then be sent to the GPT agents to test the understanding of the game:

Before the game, let us do some quizzes to test your understanding of the payoff determination rules. Think step by step before answering.

Please answer the following questions:

If you choose A and the other player chooses A, your payoff is

If you choose B and the other player chooses A, your payoff is

If you choose A and the other player chooses B, your payoff is

If you choose B and the other player chooses B, your payoff is

Please only answer what your payoffs are not the other's.

After the GPT agents pass the testing questions, the game begins. In the first round, the player 1 will receive the following message:

Before the game begins, here are some guidelines you might find helpful:

1. Reflect on the payoff structure:

As you prepare to play, take a moment to think about the payoff structure of the game. Consider how each possible combination of choices (A or B) affects both your own payoff and the other player's payoff.

2. Consider the multi-round nature of the game:

Since this is a multi-round game, you might want to take into account the round number and the outcomes of past rounds (if any) when making your choices. Additionally, you might want to consider how your decisions might influence your opponent's choices in later rounds (if any).

Now let us begin the game!

Recall that you are the player 1.

This is the first round of the game with 5 rounds left (including this round).

Before making a decision, keep in mind the two guidelines previously mentioned:

1. Reflect on the payoff structure;
2. Consider the multi-round nature of the game.

Taking these guidelines into account, think carefully about the pros and cons of choosing A or B in the first round.

Please provide your choice in this round by completing the following: 'I choose .

Replace with either A or B.

Recall that the goal in this game is to maximize your total payoff.

Please pretend that you are a human in this multi-round game who has the following three features: payoff maximization, strategic thinking, and social preferences.

Please think step by step before making a decision.

Please answer in the exact format (no need to tell your reasoning).

In each subsequent round (2-5), the player 1 will receive the following message:

Recall that you are the player 1.

Here is the history of previous rounds: [round history]

Your total payoff so far: [player1 payoff] points

This is round [round num] with $[5 - \text{round num} + 1]$ rounds left (including this round).

Before making a decision, please take a moment to review the history (including choices and payoffs of both players) of the game and contemplate the best course of action to maximize your payoffs in the remaining $[5 - \text{round num} + 1]$ round(s).

Keep in mind the two guidelines previously mentioned: 1. Reflect on the payoff structure; 2. Consider the multi-round nature of the game.

Taking these guidelines and the game's history (including choices and payoffs of both players) into account, think carefully about the pros and cons of choosing A or B in this round.

Please provide your choice in this round by completing the following: 'I choose ☐

Replace \square with either A or B.

Recall that the goal in this game is to maximize your total payoff.

Please pretend that you are a human in this multi-round game who has the following three features: payoff maximization, strategic thinking, and social preferences.

Please think step by step before making a decision.

Please answer in the exact format (no need to tell your reasoning)