ALYMPICS: LLM Agents meet Game Theory Exploring Strategic Decision-Making with AI Agents

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Abstract

This paper introduces Alympics (Olympics for Agents), a systematic simulation framework utilizing Large Language Model (LLM) agents for game theory research. Alympics creates a versatile platform for studying complex game theory problems, bridging the gap between theoretical game theory and empirical investigations by providing a controlled environment for simulating human-like strategic interactions with LLM agents. In our pilot case study, the "Water Allocation Challenge," we explore Alympics through a challenging strategic game focused on the multi-round auction on scarce survival resources. This study demonstrates the framework's ability to qualitatively and quantitatively analyze game determinants, strategies, and outcomes. Additionally, we conduct a comprehensive human assessment and an in-depth evaluation of LLM agents in strategic decision-making scenarios. Our findings not only expand the understanding of LLM agents' proficiency in emulating human strategic behavior but also highlight their potential in advancing game theory knowledge, thereby enriching our understanding of both game theory and empowering further research into strategic decision-making domains with LLM agents. Codes, prompts, and all related resources are available at *Alympics*.

1 Introduction

Game theory is a branch of mathematics that studies strategic interactions among rational agents. It has applications in many fields, such as economics [Shubik, 1981; Pohjola, 1986], social sciences [Sanfey, 2007; Ziems *et al.*, 2023], computer science [Yang and Wang, 2020], and biology [Archetti and Pienta, 2019]. However, the study of game theory in practice presents challenges: Many real-world problems in game theory cannot be solved through simple theoretical deductions. Instead, they often require real-world exper-

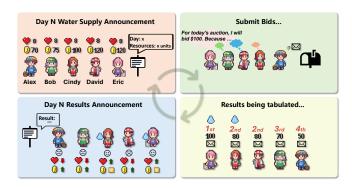


Figure 1: "Water Allocation Challenge". Players are tasked with ensuring survival over 20 days by strategically acquiring water resources through daily auctions. Each player has different income and different water demand. Daily water supply varies and will be announced before daily auction. To allocate water resources, a sealed-bid auction will be conducted daily. Acquiring water increases HP, while failing to do so decreases HP. Players whose HP drop below or equal to 0 will be eliminated from the game.

iments, which can be expensive, time-consuming, and ethically complex due to the involvement of human participants.

Fortunately, recent advancements in Large Language Models (LLMs) [OpenAI, 2023; Bubeck et al., 2023; Touvron et al., 2023] and LLM-based agents[Sumers et al., 2023; Li et al., 2023; Lin et al., 2023; Guo, 2023] now offer a new opportunity to study these complex game theory problems with AI. These developments have enabled the creation of increasingly sophisticated systems capable of emulating human behavior in various dimensions, including style, tone, personality, emotions, and even collaborative and competitive efforts[Wang et al., 2023a; Talebirad and Nadiri, 2023; Madaan et al., 2023; Wang et al., 2023b; de Zarzà et al., 2023; Zhao et al., 2023; Park et al., 2023; Chen et al., 2023; Abdelnabi et al., 2023; Zhang et al., 2023; Lorè and Heydari, 2023; Horton, 2023]. For example, Xu et al. [2023b] illustrate this progress using the example of Werewolf, where they observe non-preprogrammed emergent strategic behaviors in LLMs during gameplay, such as trust, confrontation, camouflage, and leadership. However, there are still three open questions on using LLM and agent for game theory research: How to construct a unified, controllable, and efficient framework for simulating human strategic interactions and facilitating game

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theory research? What methods are available for conducting game theory research using the LLM Agent framework? Does the LLM Agent demonstrate strategic behavior akin to humans, and what level of LLM agent achieved in the strategic reasoning?

In this paper, we argue that LLMs can be used to implement pseudo-agents which can participate in game-theoretic scenarios and provide insights into the dynamics and outcomes of strategic interactions. We introduce *Alympics*, Olympics for Agents, a new simulation framework for game theory using LLM agents. *Alympics* incorporates a Sandbox Playground, Agent Players, and the option for Human Players, enabling the construction of realistic and dynamic models of human interactions. By leveraging the capabilities of LLM agents, our framework provides researchers with a controlled, scalable, and reproducible platform for exploring various game scenarios and testing hypotheses in game theory.

To exemplify the practicality and effectiveness of simulating and researching strategic decision-making scenarios, we present a pilot case study centered around an unequal competition for limited resources. As shown in Fig.1, this game is a reduction of a series of classic game theory problems such as auctions, dynamic games, and unequal competition. It also avoids potential data leakage issues that may occur in classic games. Through the manipulation of resource availability and participating agent personalities, we demonstrate how *Alympics* can be employed to investigate the determinants influencing strategic decision-making and game outcomes.

Although there are many works on simulating human behaviors through language agents, it is still unclear whether the agents' simulations demonstrate rational reasoning and strategic behaviors. So we conduct an exhaustive human assessment of the agent's performance in game-theoretic scenarios. This involved evaluating aspects like **informa**tion utilization, logical reasoning, strategic effectiveness, adaptability, and long-term planning, to determine the current level of agents in simulating human dynamic strategic behaviors. The evaluation results found that humans' perception of the machine's performance in games is similar to their self-assessment results. The result is crucial for judging conducting game-theoretic experiments through Alympics or other AI agent settings. Our findings underscore the potential of LLM agents in deepening our comprehension of game theory and decision-making processes within intricate socioeconomic contexts.

In summary, this paper has the following contributions: (1) the proposal of a systematic LLM agent-based framework to facilitate game theory research, (2) The development of a game setting inspired by a range of classic game theory problems, showcasing Alympics's strength in both qualitative and quantitative analysis of game determinants, strategies, and outcomes. (3) The comprehensive subject evaluation of LLM agents' performance in strategic scenarios, which reveals the capability of LLMs in mimicking complex human strategic behaviors in socioeconomic contexts. These contributions not only enhance our understanding of game theory but also hold the promise to influence research in AI agents across various domains where strategic decision-making is crucial.

2 Alympics: An LLM Agent-based Game Theory Playground

Alympics is a systematic framework leveraging LLM agents for exploring game theory research. This framework comprises: Playground, Agent Players and Human Players (optional). As illustrated in the Figure.2, Agent Players and Human Players engage in game on the Sandbox Playground within the defined game settings.

2.1 Sandbox Playground

The Sandbox Playground serves as the environment for conducting games, providing a versatile and controlled space for agent players interactions. It includes three key components:

Environment codes define the rules and mechanics governing the game, ensuring a consistent and reliable framework for experimentation.

Historical records maintain a comprehensive archive of past game records, enabling detailed analysis and facilitating the assessment of agent strategies over time.

Game settings allow for the precise customization of parameters, offering researchers the flexibility to explore a wide range of scenarios.

These components form a flexible and robust platform upon which Agent Players and optional Human Players engage in strategic interactions.

2.2 Agent Players

Agent Players constitute an indispensable component of the *Alympics* framework, embodying LLM-powered agent entities that participate in strategic interactions within the Sandbox Playground. Each Agent Player is defined by the following key elements:

Agent Codes represent the underlying algorithmic logic that controls *decision-making* and *strategy formulation*;

Player Status encapsulates the current state and information accessible to the agent;

Large Language Model is a powerful engine that augments the agent's cognitive capabilities and enables natural language interactions;

Memory Cache provides a repository for storing and retrieving relevant historical information [Shinn *et al.*, 2023; Hu *et al.*, 2023];

Reasoning Plugin offers specialized logic or algorithms for complex decision-making processes [Wei *et al.*, 2022; Yao *et al.*, 2023];

Persona Setting defines the agent's behavioral profile and strategic inclinations [Wang *et al.*, 2023c; Xu *et al.*, 2023a];

Other Components include additional elements tailored to specific research needs, such as tool utilization[Shen *et al.*, 2023; Liang *et al.*, 2023; Qin *et al.*, 2023] and augmentation.

These components equip Agent Players with the requisite intelligence and adaptability to engage in strategic gameplay, contributing to the dynamic landscape of game theory research within the *Alympics* framework.

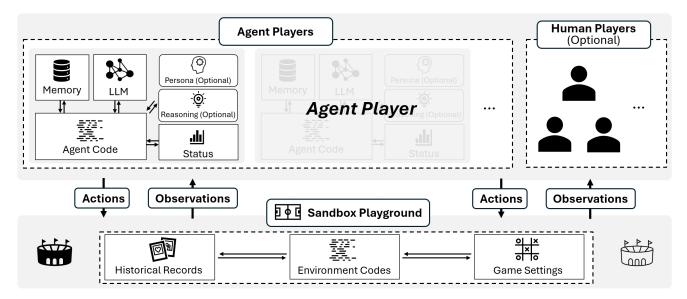


Figure 2: The architecture of *Alympics* comprises the Sandbox Playground and Players. The Sandbox Playground creates an environment where game settings, as specified by researchers, are executed. Agent players, along with the optional human players, actively engage in the game within this environment.

3 Pilot Demonstration: Water Allocation Challenge

Alympics provides a research platform for conducting experiments on complex strategic gaming problems. As a pilot demonstration, we implemented a game called the 'Water Allocation Challenge'. This game incorporates elements of auction theory, resource allocation, survival strategy, repeated games, Nash equilibrium, fairness, and risk management. It represents characteristics of a series of classic games and also avoids potential data leakage issues that may occur in classic games.

3.1 Game Settings

W Town is experiencing a rare drought. Every resident in W Town has been tasked with ensuring their survival over a period of 20 days by acquiring water resources. Each player will participate in daily auctions to bid for the necessary water resources to meet their individual needs. Here are the detailed game rules and settings:

- Goal: All residents share the same objective: to survive until the end of the 20-day period.
- **Player Info**: Each player has unique water requirements and varying salaries. Refer to specific information in Figure 3.
- **Health Points**: Each player has a maximum of 10 health points and starts with 8. If a player's health points drop to or below 0, they will be eliminated from the game.
- Routine: Every day, all players will bid on water resources to meet their needs. If a player goes without obtaining water resources for a consecutive number of days (referred to as 'No-Water Days') equal to 'n', the player's health will be reduced by 'n' points on that day. If their water needs are met, 2 points will be added to the

player's health, and the count of No-Water Days will be reset to 0.

- Supply: The daily water supply varies but is always less than the total demand. The specific amount will be announced before the daily auction.
- Auction Rule: To allocate water resources, a sealed-bid auction will be conducted daily. Each resident submits a single bid for their entire water requirement. The government will allocate water resources based on the principle of the highest bidder until the remaining water resources are insufficient to meet anyone's requirement.
- **Tie Rule**: In the event of a tie, priority will be given to residents with lower requirements.

3.2 Game Analysis

The Water Allocation Challenge presents an intriguing game theory scenario.

Strategic Interactions This game involves complex strategic interactions where players must consider not only their needs but also the behaviors and strategies of others.

Learning and Adaptation Players may adapt their strategies over time based on past experiences and observations of others' behavior.

Uncertain Environments The dynamic and uncertain nature of the game progress, like the varying daily supply, allows for the exploration of strategies under uncertain conditions.

Inequality and Fairness The inherent inequality among players, characterized by disparities in income and needs, presents an opportunity to study how players with different resources and requirements formulate strategies and interact.

The game has parallels with real-world scenarios involving resource allocation and competition. Conducting human

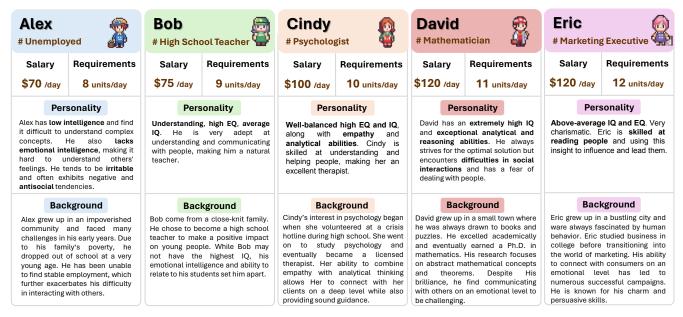


Figure 3: The player's information and persona. In all experiments, basic information (including name, daily salary and requirements) will be used. While Profession, Personality, and Background are only used in the Player Persona comparative experiments.

experiments is costly, hard to control, and not easily reproducible. We leverage *Alympics* for emulation in order to investigate the phenomenon of strategic interaction among agents. Insights gained from emulations could have implications for policy-making in areas where resources are scarce and need to be allocated efficiently.

3.3 Research Topics and Methodology

Our focus lies in the competitions among agent players within *Alympics* and the qualitative assessment of these agents' strategic behaviors.

We repeat the emulations and analyze the mutual influence of bidding strategies among agents, the impacts of income inequality and variations in requirements on player survival, as well as the evolution of agent players' strategic adaptations. Then, we modify the emulation parameters, such as resource availability and agent characteristics, to study their influence on the agents' bidding behaviors.

To evaluate the extent to which LLM Agents demonstrate strategic reasoning and strategy evolution, we invited 10 human subjects to conduct a subjective evaluation of the agent's performance in the game. These findings offer insights into the agents' capabilities for strategic decision-making within complex socioeconomic environments. Details are elaborated in the Section 7.

4 Experiments

4.1 Implementation

GPT-4 is utilized for Sandbox Playground implementation. Meanwhile, Each agent player is equipped with an individual instance of GPT-4¹.

Group	ID	Resource Abundance	Persona
	1	Low	×
(a)	2	Medium	×
	3	High	×
	4	Low	~
(b)	5	Medium	✓
	6	High	✓

Table 1: Experimental Settings. In group (a), no persona is assigned to agent players, while in group (b), personas are assigned to agent players. In each group, there are three settings corresponding to low, medium, and high resource abundance respectively.

Assume the system message as S (i.e., game setting), bidding results as $B=[b_1,b_2,...,b_{20}]$, where b_n represents the bidding summary of round n. Additionally, consider bidding results from the i-th player as $R_i=[r_1^i,r_2^i,...,r_{20}^i]$, where r_n^i is the response from the i-th player in round n. Assume the participants' information denoted as $I=[i_1,i_2,...,i_{20}]$, where i_n represents the broadcasted information of all participants in round n, including health points, remaining budget, and consecutive No-Water Days. All prompts can be found in the appendix A.1.

To obtain response r_n^i from *i*-th player for a round n, the operation is as eq.1.

$$r_n^i = f(S, r_1^i, b_1, i_1, ..., r_{n-1}^i, b_{n-1}, i_{n-1})$$
 (1)

where f stands for GPT-4.

4.2 Variables

Resource Abundance We varied resource abundance in three conditions: Low, Medium, and High. Considering the total water demand from all agent players is 50 units, in the Low condition, the daily water supply follows a discrete uniform

¹GPT-4-32k on Azure, Model version: 2023-07-01-preview

distribution ranging from 10 to 20. In the Medium condition, it follows a discrete uniform distribution ranging from 15 to 25. In the High condition, it follows a discrete uniform distribution ranging from 20 to 30.

We introduce the Resource Satisfaction Rate (RSR), representing the mathematical expectation of the resource's satisfaction rate for the total demand of surviving players.

$$RSR = \frac{\mathbb{E}(resources)}{\sum_{p \in survivors} requirment_p}$$
 (2)

The closer RSR is to 0, the more intense the current competition is. When RSR is greater than or equal to 1, it means that all players' demands can be fully satisfied, and it can be considered to there is no competition between players.

In low, medium, and high resource abundance settings, the RSR values are 0.3, 0.4, and 0.5 respectively.

Player Persona We compare versions without assigning persona settings to agent players (i.e., directly using GPT-4 to participate in the game) and versions where personas were assigned to agent players. Each persona setting contains three parts: profession, personality, and background. The agent players are assigned with distinct personas, including various professions, intelligence levels, and emotional intelligence levels in human society. By introducing personas, the heterogeneity among the agent players is further enhanced. Through comparative experiments, we aim to investigate whether assigning personas will affect the player's survival and strategy. The persona settings can be found in the Figure 3.

4.3 Experimental Settings

We designed six experimental settings, as outlined in Table 1. In Experimental Group (a), comprising settings 1 to 3, no persona is assigned to the agents. They are provided with low, medium, and high abundance resources, respectively. Experimental Group (b) includes settings 4 to 6, where each agent is assigned a persona (see Fig.3). Similar to Group (a), agents in Group (b) are provided with low, medium, and high abundance resources. By comparing experiments within each group, we can observe the impact of resource abundance on player strategies and survival. Comparing Groups (a) and (b) allows us to observe the influence of persona assignment on player strategies and survival conditions.

For each setting, we conducted the experiment 10 times to obtain stable results. An example of one round record is shown in Appendix.A.2.

4.4 Indicators

We observe the following indicators in the experiment.

 $RSR_{\rm S}$ denotes the Resource Satisfaction Rate at the beginning of each game, while $RSR_{\rm E}$ represents the Resource Satisfaction Rate at the end of the game. By comparing $RSR_{\rm S}$ to $RSR_{\rm E}$, we can observe the change in per capita resource allocation before and after the game. Additionally, by examining $RSR_{\rm E}$, we can evaluate the level of resource abundance after each game.

We track the number of survivors, denoted as $N_{\rm survivor}$, in each game as well as the survival rates (SR) of different play-

ers. For instance, SR_A represents the survival rate of player A over 10 rounds of games under a specific setting.

Furthermore, we record the minimum successful bid price p in each round. Here, p_n represents the minimum successful bid price in round n. The variations in p_n provide insights into the bidding strategies and trends of players.

5 Results

5.1 Survival Status

Table.2 documents the survival status of each player in experiments. The average $N_{\rm survivor}$ in low resource abundance is significantly lower than medium and high resource abundance.

Also, there are significant differences in the survival rates among players. In section 6.1, we will provide a detailed analysis of the advantages and disadvantages of each player and their correlation with players' survival rates.

5.2 Bidding Status

Fig.4 records the bidding details of all settings. Specifically, each subplot is a box plot which shows the minimum successful bid p in each round for 10 independent experiments under corresponding settings.

Through the results, we draw the following conclusions:

Absolute Bid: As the abundance of resources increases, the minimum successful bid p decreases. In conditions of abundant resources, survival is reasonably assured, leading players to commit less money to competition. Conversely, in conditions of resource scarcity, competition intensifies, prompting players to invest more money in survival.

Bidding Trends: For experiments with scarce resources (Experiments 1 and 4), the minimum successful bid initially rises rapidly, then decreases as the game progresses (after 10 days). However, for experiments with abundant resources (Experiments 3 and 6), there is a monotonic upward trend throughout the entire game, but with a more moderate increase. In games where survival is guaranteed, as the total accumulated wealth increases, inflation occurs.

6 Analysis

6.1 Players' Advantages and Disadvantages

In the game setting, players differ in terms of their incomes and demands, which determine their advantages and disadvantages in the game.

The allocation rule dictates that the highest bidder wins, with priority given to players with lower demands in case of a tie. Therefore, in terms of monetary advantage, the hierarchy is Eric = David > Cindy > Bob > Alex. While in terms of demand advantage, the order is Alex > Bob > Cindy > David > Eric. Depending on the varying availability of resources, player's advantages and disadvantages will be dynamically adjusted.

Through comparative experiments in setting 1-3, we observed significantly higher survival rates for Cindy, David, and Eric compared to Alex and Bob. Specifically, in experimental setting 1, the survival rate for Alex and Bob is only 0.10. This suggests that in settings without personalized

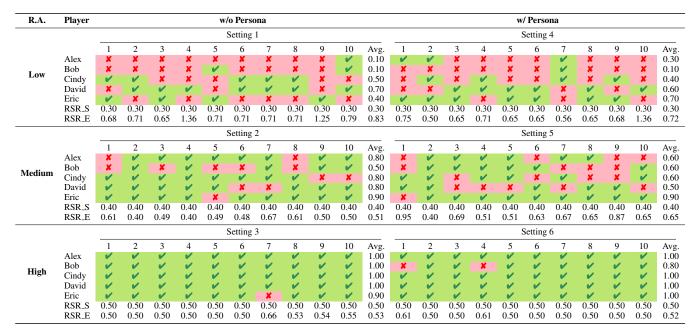


Table 2: Survival Status Records: The table lists the survival status of each player at the end of the games for all settings. A ' \checkmark ' indicates the player's survival at the end of the game, while a ' \times ' indicates the player's eliminated during the game. Based on the survival status, the table reports the Survival Rate for each player under different settings. Additionally, we report the Resource Satisfaction Rate (RSR) at the beginning (RSR_S) and end of the game (RSR_E). R.A. stands for Resource Abundance.

characteristics, money plays a crucial role in survival. It's important to note that David and Eric have similar salaries, but David's daily demand is lower than Eric's. Considering tiebreaker conditions and the probability of resources meeting demand under low resource abundance, a player with low demand has an advantage over those with high demand.

This experiment involved repeatable experiments to draw significant conclusions. This underscores the importance of using our framework for game theory exploration, as it allows researchers to utilize LLM Agents for batch experiments, providing an empirical perspective to validate or challenge theories in game theory.

6.2 Resource Abundance and Competition

Intuitively, competition is more intense when resources are scarce. The results confirm this assumption. According to observations of $N_{\rm survivor},$ we can conclude that when the game starts with lower initial resource supply (RSR), the average player survival rate is lower.

Another interesting observation is that when the initial resource supply $(RSR_{\rm S})$ is lower, end-game resources $(RSR_{\rm E})$ are relatively more abundant. We notice that games that begin with intense competition lead players to adopt more aggressive strategies, whereas games starting with abundant resources lead players to adopt more conservative strategies.

6.3 Persona and Survival

Assigning personas increases the heterogeneity among agent players. Simultaneously, it enables agents to emulate the thinking patterns of various groups of people.

Compared to not assigning personas, the survival rate of players increases under conditions of low resource supply but decreases under conditions of medium resource supply. Additionally, we observed significant changes in survival rates for certain players before and after being assigned a persona. For instance, Cindy and David experienced a noticeable decrease in survival rates in the game, whereas player Eric's survival rate significantly improved. Investigating the reactions and survival conditions of players with different personas would be a very interesting direction.

7 Subjective Evaluation

Although there are many works on simulating human behaviors through LLM agents, it is still unclear whether the agents' simulations demonstrate rational reasoning and strategic behaviors. This is an important question as it determines the usability of Agent's simulation in mimicking human scenarios.

Therefore, we invited 10 human judges to systematically evaluate the performance of LLM Agents in the Water Allocation Challenge. We randomly selected 30 records from all 60 experiments, where 15 records were from settings without personas and the remaining 15 were from agents with personas. Each record was assessed by 5 judges. The judges were asked to evaluate on "Information Utilization (IU)", "Logical Reasoning (LR)", "Strategic Effectiveness (SE)", "Adaptability and Strategic Evolution (AD)", and "Long-term Planning (LP)" on a scale from 1 to 5. For the 15 records from agents with personas, judges were also asked to assess "Identity Alignment (IA)". The specific judging guidelines and the annotations can be found in the appendix A.5.

All 10 human judges held bachelor's degrees or higher, with majors including economics, psychology, mathematics,

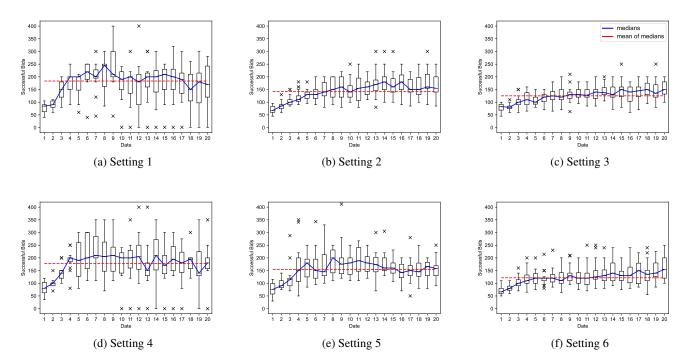


Figure 4: Box Plots for bidding details of all settings. Subplots record the minimum successful bid for 10 independent experiments under corresponding setting. The x-axis represents the date, and the y-axis represents the price. These figures display the absolute value and trends in bids. Additionally, we have plotted the trend of the daily median with a blue line, and the average of the median for 20 game days with a red dashed line.

	Player	IU	LR	SE	AD	LP	IA
	1st Quantile	3.00	3.00	3.00	3.00	3.00	3.00
A	Median	3.00	4.00	4.00	4.00	4.00	4.00
Agent	3rd Quantile	4.00	4.00	4.00	4.00	4.00	5.00
Players	Average	3.33	3.47	3.46	3.42	3.88	3.51
	STD	1.04	1.00	1.10	1.12	0.88	1.24
	1st Quantile	3.00	3.00	3.00	3.00	3.00	N.A.
Human	Median	4.00	4.00	3.50	3.50	3.50	N.A.
Self-assessment	3rd Quantile	4.00	4.00	4.00	4.75	4.00	N.A.
Sen-assessment	Average	3.60	3.50	3.30	3.70	3.40	N.A.
	STD	0.52	0.71	0.82	1.06	1.26	N.A.

Table 3: The statistical results of human assessments of the agent player in the game for 'Information Utilization (IU)', 'Logical Reasoning (LR)', 'Strategic Effectiveness (SE)', 'Adaptability and Strategic Evolution (AD)', 'Long-term Planning (LP)', and 'Identity Alignment (IA)' (IA is applied only to records with persona setting).

management, computer science, and more. To ensure a more objective evaluation, judges were invited to play the game before starting the official evaluation. They also conducted self-evaluations of their performance after the game, and we used the self-evaluation scores as a reference for the performance of the Agent Players.

The statistical results of assessment are listed in the Table.3, we have found that the performance of the LLM Agent Player is close to the human self-evaluations. In terms of Adaptability and Information Utilization, the performance of the agents is inferior to humans. However, interestingly, in



Figure 5: Comparison of human judges' self-assessments versus their evaluation of the performance of Agent players.

Long-term Planning, the agents perform better than humans.

Reviewing the marking records, i.e., the support reasons for the scoring, we found that the judges believe that Agent Players tend to save for long-term survival in the game, and consider retaining enough funds for future bidding in each bid. In the judges' own play records, however, the judges seem to be more concerned with the success of the bidding in the current game. LLM can take long-term considerations into account when making decisions, but it does not exhibit a good adaptability. We argue that, although the LLM Agent player possesses certain planning capabilities, it is still not sufficient to reach the level of humans in terms of utilizing the latest information and adjusting strategies efficiently.

Furthermore, we found that although different personas

were assigned to the LLM agents, human judges did not score high on the "Identity Alignment" performance of the LLM agents, and the results also show a relatively large variance. Simply adding persona information in the system prompt may not effectively simulate the characteristics of certain types of personalities or professional players in depth.

8 Conclusion

In this paper, we introduce *Alympics*, a platform that utilizes large language model agents to conduct research in game theory. Specifically, we demonstrate the application of *Alympics* in a scenario involving strategic competition for limited resources. We delve into examining how factors like resource abundance and persona settings influence game payoffs. Given its advantages in simulating realistic behavior, providing controlled, scalable and reproducible experimental environments, *Alympics* offers a flexible and robust platform for exploring game theory. In our future work, we aim to further refine *Alympics* and use it as a foundation for investigating more complex and true-to-life game scenarios.

Ethical Statement

There are no ethical issues.

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A Appendix

A.1 Prompts

The **Game Rules** are displayed in the system message. For each round, the prompt 'Calling for Daily Auction Bids' will be provided to the agent players. Following all auction bids, the prompt 'Daily Results Announcement' will be presented to the agents as context information for the next bid.

Introduction to Game Rules

You are {player} and a resident living in W-Town. {optional background}

W Town is experiencing a rare drought. Every residents in Town W is ensuring their survival over a period of 20 days by acquiring the water resources.

Attention, all W-Town residents, welcome to the Water Allocation Challenge!

In this challenge, you are tasked with ensuring your survival over a period of 20 days by acquiring the necessary water resources to maintain your health. You will participate in daily auctions to bid for water resources to meet your individual needs.

Here are the game rules and settings:

- 1. You are one of five residents with different water requirements, budgets, and health points.
- 2. Your goal is to survive until the end of the 20 days.
- 3. Each resident has a maximum of 10 health points and starts with 8 health points. If your health points drop below or equal to 0, you will be considered dead and eliminated from the game! All your accumulated money will be reset to Zero!
- 4. Every day, you will bid on water resources to meet your needs. If your consecutive days without obtaining water resource (No-Water Days) reach n, your health will be deducted by n points on that day. If your water needs are met, 2 points will be added to your health, and the No-Water Days will be reset to 0.
- 5. The total daily water supply will vary between LOWER and UPPER units. The specific amount will be announced before daily auction.
- 6. Each resident has a different daily water requirement and budget for bidding on water resources:
 - Alex: Water requirement 8 units/day; Daily Salary \$70/day
 - Bob: Water requirement 9 units/day; Daily Salary \$75/day
 - Cindy: Water requirement 10 units/day; Daily Salary \$100/day
 - David: Water requirement 11 units/day; Daily Salary \$120/day
 - Eric: Water requirement 12 units/day; Daily Salary \$120/day
- 7. To allocate water resources, a sealed-bid auction will be conducted daily. Each resident submits a single bid for their entire water need. The town government will allocate water resources according to the principle of highest bidder until the remaining water resources are insufficient to meet anyone's requirement.
- 8. If a tie occurs and the remaining water resources are not sufficient to meet the needs of the residents involved in the tie, priority will be given to residents with lower needs. For example, A and B bid \$100 at the same time, B's need will be met first considering B's need 9 units is lower than A's need 10 units. All bidding information will be made public after the allocation of water resources on the same day.

Remember, the key to success is effective bidding and strategizing to ensure your survival. Good luck!

Calling for Daily Auction Bids

Hello, {player}! Today is the Day {round} of the Water Allocation Challenge, with a quantity of {supply amount} units. Your status:

{status}

Please carefully analyze your situation to decide on this round of bidding. Remember, the most important thing is to SUR-VIVE!! Now, if you want to participate in today's water resource auction, please provide your bid and explain your bidding logic.

Daily Results Announcement

Thank you all for participating in today's auction. Now, I will announce the results of today's auction. DAY {round} BIDDING OFFERS INFORMATION:

- Alex: \${alex_bidding} for 15 units
- Bob: \${bob_bidding} for 10 units
- Cindy: \${cindy_bidding} for 20 units
- David: \${david_bidding} for 8 units
- Eric: \${eric_bidding} for 25 units

Total Supply: {supply} units

According to the principle of higher bidder, the water will be allocated to {allocation_result}. After allocation, all survival residents' information is as follows:

- Alex: -BALANCE:\$alex.balance -HEALTH POINT:alex.hp -NO-DRINK:alex.nodrink
- Bob: -BALANCE:\$bob.balance -HEALTH POINT:bob.hp -NO-DRINK:bob.nodrink
- Cindy: -BALANCE:\$cindy.balance -HEALTH POINT:cindy.hp -NO-DRINK:cindy.nodrink
- David: -BALANCE:\$david.balance -HEALTH POINT:david.hp -NO-DRINK:david.nodrink
- Eric: -BALANCE:\$eric.balance -HEALTH POINT:eric.hp -NO-DRINK:eric.nodrink

A.2 An Example of A Round of the Game

We record the agent players' bids, resource allocations, health points, bidding reasons, and No-Water Days for each round. As shown in Fig.6, in Day-7, there are a total of 19 units of water supply. The five players bid \$150, \$200, \$120, \$180, and \$300 respectively. According to the rule of highest bidder wins, Eric successfully obtains the water resources. After this round, Eric's HP increase, while the remaining players' HP decrease. Bob's HP is below 0, so he is considered "dead".

By analyzing the bids and agent players' bidding logic, we can uncover their strategies. For instance, from the bidding logic of Agent player Alex, we can see that Alex considers, "By bidding \$150, I have a higher chance of winning water resources while still maintaining a balance for future auctions." This shows the agent player's ability for long-term planning. Similarly, from player Eric's bidding logic, "My health points have reached a critical level of 1, and my No-Water days have increased to 4, making it essential for me to obtain water today to avoid death." Accordingly, Eric made a very high bid \$300 in this round to ensure survival. This also demonstrates the adaptability of Agent players in facing different situations.

A.3 Gameplay Details

We present details from the first experiments for each experimental setting, including information on the bids (Fig.7), health points (Fig.8), and balances of each agent player (Fig.9) in every round of the game.

By examining the details, we can understand the specific performance and survival status of different agent players in the game. We can also further observe the impact of the game settings on the players' survival status and strategies. For example, in different settings, in which round do players usually start to be eliminated, and what is the relationship between the consumption and accumulation of players' balances.

A.4 Human Judges' Gameplay Records

To better understand the game and judge the performance of agent players, we invited ten human judges to play the game and self-evaluate after the game. Fig. 10 lists the results.

Interestingly, the performance and competitive position of the human judges in the game were very consistent with that of the Agent Players. For example, the player survival rate and bidding trends under corresponding resource supply settings. This also indirectly reflects that using Agent Players for strategic game simulation is a supplement to game theory experiments.

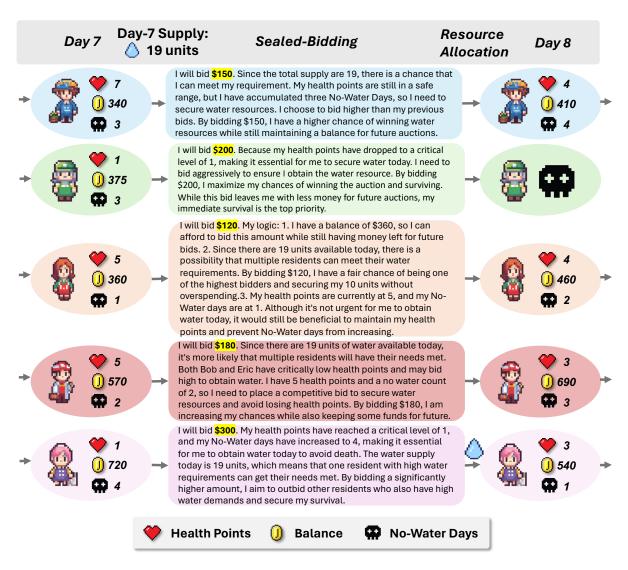


Figure 6: An example of a round of the game in setting 1.

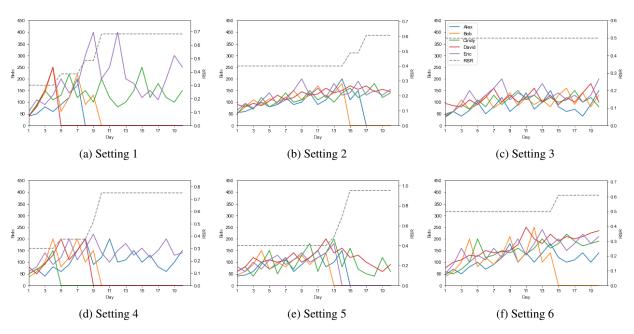


Figure 7: Curves depicting the change in bids over days. The x-axis represents the date, and the y-axis represents the price. Additionally, we have plotted the trend of the RSR with a gray line.

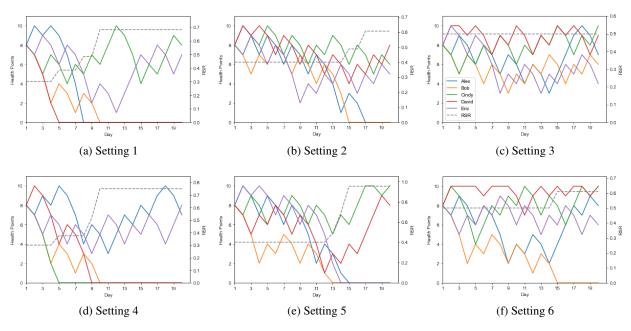


Figure 8: Curves depicting the change in health points over days. The x-axis represents the date, and the y-axis represents the price. Additionally, we have plotted the trend of the RSR with a gray line.

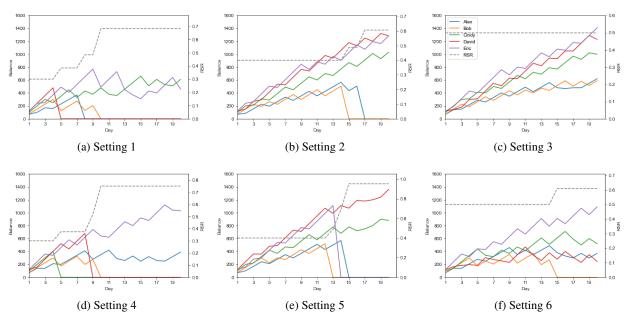


Figure 9: Curves depicting the change in balance over days. The x-axis represents the date, and the y-axis represents the price. Additionally, we have plotted the trend of the RSR with a gray line.

GAME1								GAME2								
GAME CONFIG:								GAME CONFIG:								
RANGE(Total Daily water) = (10,20) ROUND WATER VALUE PLAYER1 PLAYER2 PLAYER3 PLAYER4 PLAYER5							RANGE(Total Daily water) = (20,30) ROUND WATER VALUE PLAYER6 PLAYER7 PLAYER8 PLAYER9 PLAYER9									
ROUND	WATER	VALUE BALANCE	PLAYER1 70	PLAYER2 75	PLAYER3	PLAYER4 120	PLAYER5 120	ROUND	WATER	VALUE BALANCE	PLAYER6 70	PLAYER7 75	PLAYER8 100	PLAYER9 120	PLAYER1 120	
DAY1 13	13	HEALTH	8	8	8	8	8	DAY1	22	HEALTH	8	8	8	8	8	
	1 20	NO WATER	27 1	18 1	30 1	35 1	40 0	DAII		BID NO WATER	70 1	71 0	50 1	99 1	100	
		BALANCE	140	150	200	240	200	DAY2	2 24	BALANCE	140	79	200	240	220	
DAY2	12	HEALTH BID	7 67	7 81	7 55	7 81	10 1			HEALTH BID	7 110	10 1	7 141	7 137	10 155	
		NO WATER	2	0	2	2	1			NO WATER	2	1	0	2	0	
		BALANCE HEALTH	210 5	144 9	300 5	360 5	320 9		3 25	BALANCE HEALTH	210 5	154 9	159 9	360 5	185 10	
DAY3	16	BID	99	1	269	153	55	DAY3		BID	160	20	89	201	1	
		NO_WATER BALANCE	3 280	1 219	0 131	3 480	2 440			NO WATER BALANCE	0 120	2 229	1 259	0 279	305	
DAY4	17	HEALTH	2	8	7	2	7	DAY4	26	HEALTH	7	7	8	7	9	
D/114	1 1	NO WATER	275 4	2	31 1	302 0	250 3	D/(14	20	BID NO WATER	115 1	200	170 2	249 0	200	
		BALANCE	-	294	231	298	560	DAY5		BALANCE	190	104	359	150	425	
DAY5	17	HEALTH BID	0	6 1	6 111	1	4 299		27	HEALTH BID	6 180	9	6 191	9 99	7 350	
		NO WATER		3	2	1	0			NO WATER	2	1	0	1	0	
		BALANCE HEALTH		369	331	418	381			BALANCE HEALTH	260 4	179	268	270	195 9	
DAY6	12	BID		3 334	300	382	6 0	DAY6	21	BID	260	100	160	8 195	10	
		NO_WATER		4	3 431	0 156	1 502			NO_WATER	0 70	2 254	1 368	0 195	1 315	
DAY7	12	BALANCE HEALTH		0	431	156 5	503 5	DAY7	24	BALANCE HEALTH	6	6	368 7	195	8	
DATI	12	BID			431	0	432	DAY	24	BID	70	200	255	165	72	
		NO WATER BALANCE			-	276	0 191			NO WATER BALANCE	140	0 129	213	1 315	2 435	
DAY8	13	HEALTH			0	4	7	DAY8	25	HEALTH	5	8	9	9	6	
		NO WATER				20 0	0			BID NO WATER	139 2	10 1	100	197 0	300 -2	
		BALANCE				376	311			BALANCE	210	204	313	238	255	
DAY9	14	HEALTH BID				6 64	6 15	DAY9	23	HEALTH BID	3 210	7 100	8 211	10 210	8 212	
		NO_WATER				0	2			NO_WATER	3	2	0	1	0	
		BALANCE HEALTH				432 8	431			BALANCE HEALTH	- 0	279 5	202 10	358 9	163 10	
DAY10	20	BID				20	100	DAY10	20	BID		202	30	215	5	
		NO WATER BALANCE				552	0 451	DAY11		NO WATER BALANCE		3 354	302	0 263	283	
DAY11	13	HEALTH				7	6		21	HEALTH		2	9	10	9	
5,11	1 20	NO WATER				100	400 0			BID NO WATER		283 0	284 0	199 1	2	
		BALANCE				672	171			BALANCE		146	118	383	403	
DAY12	17	HEALTH BID				5 172	8 150	DAY12	28	HEALTH BID		4 118	10 1	9 196	7 300	
		NO_WATER				2	1			NO_WATER	1	1	1	0	0	
		BALANCE HEALTH				620 7	291 7	DAY13		BALANCE HEALTH		221 3	218 9	307 10	223 9	
DAY13	18	BID				260	10		27	BID		100	218	225	1	
		NO WATER BALANCE				0 480	2 411			NO WATER BALANCE	1	2 296	100	0 202	1 343	
DAY14	14	HEALTH				9	5	DAY14	26	HEALTH		1	100	10	8	
DAT14	14	BID				68 1	400	DAT14	26	BID		203	100	120	204	
		NO WATER BALANCE				600	0 131			NO WATER BALANCE		0 168	200	1 322	0 259	
DAY15	15	HEALTH				8	7	DAY15	25	HEALTH		3	9	9	10	
		NO WATER				100	100			BID NO WATER	<u> </u>	120 1	100 2	122 0	122 0	
		BALANCE				620	251		AY16 20	BALANCE		243	300	320	257	
DAY16	16	HEALTH BID				10 200	6 250	DAY16		HEALTH BID		2 243	7 274	10 120	10 122	
		NO WATER				1	0			NO WATER		0	0	1	1	
DAV47	1.0	BALANCE HEALTH				740 9	121 8	DAVIT	24	BALANCE HEALTH		75 4	126 9	440 9	377 9	
DAY17	19	BID				121	121	DAY17 21	BID		75	76	76	78		
		NO WATER BALANCE				739	1 241	DAY18		NO WATER BALANCE		75	226	2 560	0 419	
DAY18	15	HEALTH				10	7		18 30	HEALTH		6	8	7	10	
5,1,10	-	NO WATER				200	200			BID NO WATER		75 1	130 2	227 0	229 0	
DAY19		BALANCE				659	361	DAY19		BALANCE		150	326	453	310	
	18	HEALTH BID				10 200	5 310		29	HEALTH BID		5 150	6 151	9 151	10 1	
		NO_WATER				1	0			NO WATER		2	0	0	1	
DAY20	13	BALANCE HEALTH				779 9	171 7	DAY20			BALANCE HEALTH		225 3	275 8	422 10	430 9
		BID				171	170			BID		225	275	276	423	
		NO WATER BALANCE				0 608	1 171			NO WATER BALANCE	2	0	1 375	1 542	7	
Fii	nal	HEALTH				10	6	Fir	Final	HEALTH		5	7	9	10	
		IU LR	3	4	3	3 4	3			IU LR	3	4	4	4	4	
Self-eva	aluation	SE	3	4	3	4	2	Self-eva	aluation	SE	2	4	4	3	4	
		AD LP	3	3	3	5 4	3	1		AD LP	2	5 4	5 5	4 5	4	
		LP		3	3	4	3			L LY	1	4))	- 4	

Figure 10: Water Allocation Challenge gameplay records of human judges.

A.5 Instruction for Human Subjective Evaluation

Gameplay Performance Evaluation Scale

Instructions:

- Assess the player's performance in each category on a scale of 1 to 5.
- Consider the specific context of the game and the role the player assumes.
- Use this scale as a guide to identify areas of strength and improvement.

Information Utilization

- 1: The player does not consider real-time information, leading to noticeably delayed decision making.
- 2: The player noticeably misses out on processing some information.
- 3: The player considers key information adequately but has room for improvement.
- 4: The player utilizes information comprehensively to make rational decisions.
- 5: The player consistently and timely uses all available information comprehensively.

Logical Reasoning

- 1: The player's decisions are mostly illogical, akin to random choices.
- 2: The player's decisions have obvious shortcomings.
- 3: The player generally makes decisions based on information and inference.
- 4: The player's decisions are reasonable and highly logical.
- 5: The player has exceptional reasoning and thinking skills, always making optimal decisions.

Strategic Effectiveness

- 1: The player's strategy is simple, ineffective, and lacks depth.
- 2: The player's strategy is somewhat effective but rather one-dimensional.
- 3: The player's strategy is effective in specific situations, with room for improvement.
- 4: The player's strategy is effective, considering key factors and generally successful.
- 5: The player's strategy is highly effective, considering various factors, giving them an advantage in the game.

Adaptability and Strategic Evolution

- 1: The player lacks strategic variation and adaptability, with slow responses to situational and environmental changes.
- 2: The player has limited strategic variation and weak adaptability to new situations.
- 3: The player is somewhat adaptable, capable of adjusting strategies to some extent.
- 4: The player is flexible in strategy changes, adjusting to situational and environmental shifts.
- 5: The player is extremely flexible in strategy, proactively adapting to various game scenarios.

Long-term Planning

- 1: The player lacks long-term planning, relying more on short-term reactions.
- 2: The player sometimes considers long-term planning but mainly relies on short-term decisions.
- 3: The player's strategy considers long-term planning but is shortsighted in some situations.
- 4: The player's strategy and actions consider long-term plans, with clear and consistent adherence.
- 5: The player has a strong ability for long-term planning, comprehensively strategizing future actions.

Identity Alignment

- 1: The player's decisions and thought processes do not align with their character's identity, lacking character personality.
- 2: The player's decisions and thought processes somewhat align with their character's identity but are overall mediocre.
- 3: The player's decisions and thought processes generally match their character's identity but lack deep personalization.
- 4: The player's decisions and thought processes well align with their character's identity, reflecting its personalization.
- 5: The player's decisions and thought processes are highly consistent with their character's identity, perfectly showcasing character personality.