COMSCI/ECON 206 — Final Research Proposal

Innovative Play in Game Theory and Mechanism Design: An Interdisciplinary Study

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Contribution to Sustainable Development Goals (SDGs)

This project contributes primarily to

- **SDG 10: Reduced Inequalities** by examining how game-theoretic mechanism design, supported by AI-based simulation, can facilitate fairer and more inclusive resource allocation. Additionally, by integrating theoretical modeling with agent-based experimentation
- **SDG 16: Peace, Justice, and Strong Institutions**, as it seeks to promote decision-making systems that are not only efficient but also socially equitable, transparent, and aligned with principles of justice and institutional integrity.

Acknowledgments

I would like to sincerely thank **Professor Luyao Zhang** for her detailed and constructive feedback, which helped clarify inconsistencies between game representations, refine payoff rules, and improve the clarity of figures and theoretical alignment. I am also grateful to **Shiqi Chen** and **Boyan Zhang** for their insightful peer reviews, which strengthened the project's interdisciplinary coherence and analytical rigor. Special thanks to **Peilin Wu**, **Chenlei Tao**, and other group members for their valuable discussions and game collaboration. Their collective feedback significantly enhanced both the clarity and depth of this study.

I also acknowledge the valuable support of AIGC tools and open-source communities that enabled this project, including Python, Jupyter/Google Colab, NashPy, QuantEcon, Game Theory Explorer (GTE), oTree, Matplotlib, Git & GitHub, and LLM agents (e.g., GPT-4, Doubao, DeepSeek, Qwen).

Disclaimer

This project is the final research proposal submitted to COMSCI/ECON 206: Computational Microeconomics, instructed by Prof. Luyao Zhang at Duke Kunshan University in Autumn 2025.

Statement of Intellectual and Professional Growth

Through this interdisciplinary project, I advanced my ability to design and analyze strategic interaction by integrating game theory, mechanism design, and computational experimentation. 1) Developing a Bayesian bargaining model and extending it with machine learning algorithms deepened my understanding of how **data-driven methods** can **simulate and explain social behaviors** such as fairness, cooperation, and bounded rationality. 2) By applying **reinforcement learning** and **supervised modeling** to compare human and AI negotiation patterns, I strengthened my technical mastery in model training, evaluation, and interpretation within a **social-scientific framework**. 3) Collaborating with peers and engaging in discussions on ethical implications, including **algorithmic bias** and **welfare trade-offs**, enhanced my **communication** and **reflective judgment**. Overall, this project enriched my intellectual development by merging quantitative rigor with social insight, and it fostered professional growth through collaborative research, responsible innovation, and clear interdisciplinary communication.

How the project enhanced my skills in applying machine learning to social science：

- **Modeling Human Behavior:** Learned to apply reinforcement learning and supervised models to simulate human bargaining behavior, capturing adaptation, cooperation, and fairness dynamics.
- **Experiment–Simulation Integration:** Used ML models to complement oTree-based human experiments, comparing algorithmic learning trajectories with real-world decision data.
- **Algorithmic Fairness:** Reflected on how model bias and outcome disparities can influence welfare assessments, enhancing awareness of ethical considerations in computational social science.

Part 1. Strategic Game Foundations

In the **traditional simultaneous-demand bargaining game**, two players negotiate over how to split a fixed resource, such as a sum of money. Each player simultaneously submits a demand specifying the amount of the resource they wish to receive. The outcomes are determined as follows:

- If the sum of the two demands is less than or equal to the total resource, each player receives the amount they demanded.
- If the sum of the demands exceeds the total resource, neither player receives anything.

Since both players make their demands simultaneously without knowing the other's choice, the game introduces strategic uncertainty and emphasizes the importance of anticipating the opponent's behavior . (Osborne and Rubinstein, 1994).

In this project, I extend the classic simultaneous-demand game in two main ways to explore more complex strategic environments. First, I introduce an **incomplete information structure**, where each player has a **private minimum acceptable demand** and only knows the probability distribution over the other player's minimum. This modification requires players to form beliefs about the other's likely demands and make decisions under uncertainty, effectively turning the game into a **Bayesian simultaneous-move scenario**. Second, while the baseline analysis focuses on a total resource of 100, I also plan to investigate the effects of **varying the resource cap**, considering values such as 10, 100, and 1000. This allows for an examination of how the scale of available resources influences equilibrium outcomes, efficiency, and fairness.

Formally, the baseline game (with S = 100) can be described as follows:

- **Players:** Two players, $i \in \{A, B\}$
- **Resource:** Total resource $S = 100$ (baseline; later experiments will vary S)
- **Actions:** Each player simultaneously chooses a demand $d_i \in [0,S]$
- **Information Structure:** Each player has a private minimum demand t_i, and the opponent only knows the other's probability distribution F_j.
- **Payoff Function:**

$$u_i(d_i, d_j) = \begin{cases} d_i, & \text{if } d_i + d_j \leq S \\ 0, & \text{if } d_i + d_j > S \end{cases}$$

- **Timing:** Players make their demands simultaneously; payoffs are realized according to the rule above.

Through this framework, the project investigates how strategic uncertainty and the scale of resources jointly shape player behavior, equilibrium structure, and overall efficiency.

1.1 Theoretical solutions

In this game, each player has a private type representing their minimum acceptable demand, and players do not know the other's exact type. Instead, they only know the probability distribution over the opponent's type. Because of this uncertainty, a player's best choice depends not on the opponent's actual action, but on the expected outcomes across all possible types.

Consequently, the **standard Nash Equilibrium**, which assumes complete information, is **no longer sufficient to describe optimal behavior.** This setting requires an equilibrium concept that accounts for strategic uncertainty due to private information, leading naturally to the **Bayesian Nash Equilibrium (BNE)**. In a BNE, each player chooses a strategy function mapping their type to a demand, and no player can improve their expected payoff by unilaterally changing this function.

1.1.1 Equilibrium Concept: Bayes–Nash Equilibrium (BNE)

- **Definition:** A strategy profile $s^* = (s_1^*, \ldots, s_n^*)$ constitutes a Bayes–Nash Equilibrium if, for every player $i \in N$, every type $\theta_i \in \Theta_i$, and given beliefs about other players' types induced by the common prior $p(\theta)$, the strategy $s_i^*(\theta_i)$ maximizes the expected utility of player i:

$$\mathbb{E}_{\theta_{-i}\sim p(\cdot|\theta_i)}\Big[u_i(s_i^*(\theta_i), s_{-i}^*(\theta_{-i}); \theta_i)\Big] \geq \mathbb{E}_{\theta_{-i}\sim p(\cdot|\theta_i)}\Big[u_i(s_i(\theta_i), s_{-i}^*(\theta_{-i}); \theta_i)\Big]$$

for all alternative strategies s_i.

Here:

$N = \{1,2\}$ (two bargainers).

Θ_i = type space of player i, e.g., risk aversion or fairness preference.

$S_i : \Theta_i \rightarrow A_i$, mapping from types to actions (proposals/acceptances).

u_i = payoff function (depends on final allocation and type).

1.1.2 Analytical solution

- **Equilibrium Characterization:**

In the incomplete-information Bayesian version, each player has a private minimum acceptable demand t_i, unknown to the opponent, who only knows the probability distribution over t_i. Players choose a strategy function $d_i(t_i)$ mapping their type to a demand.

A Bayesian Nash Equilibrium (BNE) is characterized by the property that, for every player i and type t_i:

$$d_i(t_i) = \arg\max_{d_i} \mathbb{E}_{t_{-i}}\left[u_i(d_i, d_{-i}(t_{-i}))\right]$$

  - That is, each player's chosen demand maximizes expected payoff given beliefs about the other player's type and strategy.
  - Strategies $d_i(t_i)$ are monotonically increasing in own type: higher minimum acceptable demands lead to higher chosen demands.
  - Equilibrium balances the risk of zero payoff (over-demanding) with the potential gain of high demand. Unlike complete-information NE,

equilibrium is not a fixed pair of demands, but a function mapping private types to optimal demands.

To illustrate the Bayesian Nash Equilibrium (BNE) more concretely, consider the baseline game with total resource S=100, and players' private types $t_A \in \{30,50\}$, $t_B \in \{40,60\}$, each realized with equal probability 0.5. Each player chooses a demand $d_i(t_i) \in \{0,25,50,75,100\}$, aiming to maximize expected payoff under the feasibility rule $d_A+d_B \leq 100$.

One equilibrium obtained from the computational solver can be expressed as the following strategy functions:

sA(30)=50, sA(50)=75; sB(40)=50, sB(60)=75.

Here, both players increase their demand when facing a higher private type, consistent with the theoretical prediction that equilibrium strategies are **monotonic in type.** Given these mappings, the expected payoff for each player equals the weighted average of realized payoffs across possible type combinations. No player can increase their expected utility by deviating from this strategy function, confirming that this profile constitutes a pure Bayesian Nash Equilibrium.

- **Efficiency:**
  - Pareto Efficiency:
    - Any outcome where total demand ≤ S is Pareto efficient: increasing one player's payoff requires decreasing the other's.
    - Outcomes where total demand > S (zero payoff) are Pareto inefficient because both could be strictly better by lowering demands.
  - Utilitarian Efficiency:
    - Expected total payoff is maximized when strategies avoid over-demanding while allocating as much of S as possible.
    - The BNE strategies implicitly attempt to maximize expected sum of payoffs, given uncertainty about opponent type.
- **Fairness:**
  - Equity
    - Because each player's demand depends on their private type, realized payoffs may differ. Higher-type players receive more.
    - In expectation, fairness improves if type distributions are symmetric.
  - Envy-Freeness:
    - An allocation is envy-free if a player prefers her own payoff to the other player's payoff.
    - In this game, envy-freeness is not guaranteed, because different types may lead to asymmetric payoffs and the zero-payoff rule can generate situations where both players are worse off.

1.1.3 Interpretation

- **Realism:**
  - This Bayesian bargaining formulation reflects realistic negotiation environments where players cannot fully observe each other's constraints.
  - For example, in salary negotiations or business contracts, each side has a private minimum acceptable level (type t_i) but only probabilistic beliefs about the other's needs.
  - By incorporating incomplete information, the game captures how strategic demands emerge under uncertainty, rather than assuming perfect foresight as in the complete-information version.
- **Multiplicity of Equilibria:**
  - The game admits multiple Bayesian Nash Equilibria (BNE). In some equilibria, players demand conservatively, keeping the sum $d_A + d_B$ safely below the cap S, which guarantees positive payoffs but leaves resources underutilized.
  - In other equilibria, players demand aggressively near the cap, achieving high expected payoffs but running a greater risk of exceeding S and ending with zero. This multiplicity illustrates the tension between safety and ambition in bargaining with incomplete information.
- **Refinements:**
  - Refinements such as Perfect Bayesian Equilibrium or Sequential Equilibrium are relevant if we consider dynamic alternating-offer protocols.
  - These refinements incorporate belief updating and credible threats, narrowing down plausible equilibria and providing more predictive power. In our static one-shot proposals, BNE suffices, but dynamic versions or introducing time discounting could benefit from these refinements.

- **Bounded Rationality and Computational Tractability:**
  - In real behavior, players may not solve the Bayesian best-response problem exactly. Instead, they adopt heuristics such as "demand close to half of S" or "demand slightly above expected type." These heuristics may explain systematic deviations from equilibrium predictions:
    - Over-demanding → frequent zero-payoff outcomes.
    - Fair-split heuristics → coordination on 50-50 even when types differ, driven by norms rather than expected payoff maximization.
  - Solving for BNE requires integrating best responses over the distribution of types, which is computationally demanding even in the two-player case. Strategy adjustments must be recomputed for each cap, highlighting the need for computational tools such as NashPy for matrix-based equilibria and GTE for extensive-form comparisons. The tractability issue becomes especially salient when extending the type space or introducing richer belief structures.

1.2 Computational Results

1.2.1 Google Colab (normal form + computation)

I implemented the payoff structure of the revised simultaneous-demand bargaining game under incomplete information in a Google Colab notebook. Each player $i \in \{A,B\}$ has a private type t_i (interpreted as the player's minimum acceptable demand), drawn independently from a common-knowledge distribution — in this implementation $t_A \in \{30,50\}$ and $t_B \in \{40,60\}$, each realized with probability 0.5. Players simultaneously choose demands d_i from the discrete action set $\{0,25,50,75,100\}$.

Payoffs follow a strict feasibility rule: if $d_A+d_B \leq S$ (with $S=100$ in our runs), each player's payoff equals their own demand d_i; if $d_A+d_B>S$ then both players receive payoff 0.

- **Payoff Matrices:**
  - The displayed payoff matrices shown in **Figure 1** represent the expected utilities for each player, given their type-contingent strategy mappings. Each cell corresponds to a particular pair of pure strategies: one chosen by Player A (mapping from A's types to demands) and one chosen by Player B (mapping from B's types to demands).
  - The entries in the matrices are **expected payoffs**, not deterministic ones. Since each player's type is drawn randomly according to a probability distribution (in our case, each type occurs with probability 0.5), t**he payoffs are computed as weighted averages** over all type realizations as shown in **Figure 1**. This explains why many entries in the payoff matrices are non-integer values or decimals.
  - Thus, **the appearance of decimals** in the payoff matrices reflects the Bayesian nature of the game: **players optimize over expected rather than realized payoffs**, since they must choose strategies before knowing the opponent's type.

	t=40->0; t=60->0	t=40->0; t=60->25	t=40->0; t=60->50	t=40->0; t=60->75	t=40->0; t=60->100	t=40->25; t=60->0	t=40->25; t=60->25	t=40->25; t=60->50	t=40->25; t=60->75	t=40->25; t=60->100
t=30->0; t=50->0	0.0	0.0	0.00	0.00	0.00	0.0	0.0	0.00	0.00	0.00
t=30->0; t=50->25	12.5	12.5	12.50	12.50	6.25	12.5	12.5	12.50	12.50	6.25
t=30->0; t=50->50	25.0	25.0	25.00	12.50	12.50	25.0	25.0	25.00	12.50	12.50
t=30->0; t=50->75	37.5	37.5	18.75	18.75	18.75	37.5	37.5	18.75	18.75	18.75
t=30->0; t=50->100	50.0	25.0	25.00	25.00	25.00	25.0	0.0	0.00	0.00	0.00
t=30->25; t=50->0	12.5	12.5	12.50	12.50	6.25	12.5	12.5	12.50	12.50	6.25
t=30->25; t=50->25	25.0	25.0	25.00	25.00	12.50	25.0	25.0	25.00	25.00	12.50
t=30->25; t=50->50	37.5	37.5	37.50	25.00	18.75	37.5	37.5	37.50	25.00	18.75
t=30->25; t=50->75	50.0	50.0	31.25	31.25	25.00	50.0	50.0	31.25	31.25	25.00
t=30->25; t=50->100	62.5	37.5	37.50	37.50	31.25	37.5	12.5	12.50	12.50	6.25

	t=40->0; t=60->0	t=40->0; t=60->25	t=40->0; t=60->50	t=40->0; t=60->75	t=40->0; t=60->100	t=40->25; t=60->0	t=40->25; t=60->25	t=40->25; t=60->50	t=40->25; t=60->75	t=40->25; t=60->100
t=30->0; t=50->0	0.0	12.50	25.0	37.50	50.0	12.50	25.0	37.50	50.00	62.50
t=30->0; t=50->25	0.0	12.50	25.0	37.50	25.0	12.50	25.0	37.50	50.00	37.50
t=30->0; t=50->50	0.0	12.50	25.0	18.75	25.0	12.50	25.0	37.50	31.25	37.50
t=30->0; t=50->75	0.0	12.50	12.5	18.75	25.0	12.50	25.0	25.00	31.25	37.50
t=30->0; t=50->100	0.0	6.25	12.5	18.75	25.0	6.25	12.5	18.75	25.00	31.25
t=30->25; t=50->0	0.0	12.50	25.0	37.50	25.0	12.50	25.0	37.50	50.00	37.50
t=30->25; t=50->25	0.0	12.50	25.0	37.50	0.0	12.50	25.0	37.50	50.00	12.50
t=30->25; t=50->50	0.0	12.50	25.0	18.75	0.0	12.50	25.0	37.50	31.25	12.50
t=30->25; t=50->75	0.0	12.50	12.5	18.75	0.0	12.50	25.0	25.00	31.25	12.50
t=30->25; t=50->100	0.0	6.25	12.5	18.75	0.0	6.25	12.5	18.75	25.00	6.25

Figure 1: Payoff matrices generated in Google Colab (figure 1)

- **Solver output:**
  - In a traditional complete information version of this game, each player would know the other's type and would choose a pure best-response to that type. Here, because players only know the distribution over the other's type, they **maximize expected payoff rather than actual payoff**.
  - Consequently, **the equilibrium concept is Bayesian Nash**, not standard Nash. Each strategy in the table is type-contingent, i.e., a mapping from private type to action, which is the key feature of incomplete-information games.
  - Each equilibrium calculated in **Figure 2** corresponds to a combination of type-contingent strategies, where neither player can improve their expected payoff given their beliefs about the other's type. The multiple equilibria in **Figure 2** reflect **the discrete action set** and the fact that **different strategy combinations satisfy mutual best-response conditions**. For instance, "Pure BNE #7: A[30]=50, A[50]=50; B[40]=50, B[60]=50" is a symmetric strategy where both players demand 50 regardless of type, while other BNE show more extreme type-dependent choices.

```
=== Pure-strategy Bayesian Nash equilibria (exhaustive search) ===
Pure BNE #1: A=A[30]=0, A[50]=0  B=B[40]=100, B[60]=100  E[U]=(A:0.000000, B:100.000000)
Pure BNE #2: A=A[30]=0, A[50]=50  B=B[40]=100, B[60]=100  E[U]=(A:0.000000, B:50.000000)
Pure BNE #3: A=A[30]=0, A[50]=75  B=B[40]=100, B[60]=100  E[U]=(A:0.000000, B:50.000000)
Pure BNE #4: A=A[30]=0, A[50]=100  B=B[40]=100, B[60]=100  E[U]=(A:0.000000, B:50.000000)
Pure BNE #5: A=A[30]=25, A[50]=25  B=B[40]=75, B[60]=75  E[U]=(A:25.000000, B:75.000000)
Pure BNE #6: A=A[30]=50, A[50]=0  B=B[40]=100, B[60]=100  E[U]=(A:0.000000, B:50.000000)
Pure BNE #7: A=A[30]=50, A[50]=50  B=B[40]=50, B[60]=50  E[U]=(A:50.000000, B:50.000000)
Pure BNE #8: A=A[30]=75, A[50]=0  B=B[40]=100, B[60]=100  E[U]=(A:0.000000, B:50.000000)
Pure BNE #9: A=A[30]=75, A[50]=75  B=B[40]=25, B[60]=25  E[U]=(A:75.000000, B:25.000000)
Pure BNE #10: A=A[30]=100, A[50]=0  B=B[40]=100, B[60]=100  E[U]=(A:0.000000, B:50.000000)
Pure BNE #11: A=A[30]=100, A[50]=100  B=B[40]=0, B[60]=0  E[U]=(A:100.000000, B:0.000000)
Pure BNE #12: A=A[30]=100, A[50]=100  B=B[40]=0, B[60]=50  E[U]=(A:50.000000, B:0.000000)
Pure BNE #13: A=A[30]=100, A[50]=100  B=B[40]=0, B[60]=75  E[U]=(A:50.000000, B:0.000000)
Pure BNE #14: A=A[30]=100, A[50]=100  B=B[40]=0, B[60]=100  E[U]=(A:50.000000, B:0.000000)
Pure BNE #15: A=A[30]=100, A[50]=100  B=B[40]=50, B[60]=0  E[U]=(A:50.000000, B:0.000000)
Pure BNE #16: A=A[30]=100, A[50]=100  B=B[40]=75, B[60]=0  E[U]=(A:50.000000, B:0.000000)
Pure BNE #17: A=A[30]=100, A[50]=100  B=B[40]=100, B[60]=0  E[U]=(A:50.000000, B:0.000000)
Pure BNE #18: A=A[30]=100, A[50]=100  B=B[40]=100, B[60]=100  E[U]=(A:0.000000, B:0.000000)
```

Figure 2: Solver output from NashPy (figure 2).

1.2.2 Game Theory Explorer (extensive form + SPNE)

For illustrative purposes, we construct a **hypothetical extensive version** of the game. In this sequential version, we order the moves to allow computation of SPNE using Game Theory Explorer (GTE).

We consider a single round where Player A moves first and Player B moves second. Both players choose demands from the discrete action set {0,50,75,100}(Too many nodes can prevent GTE from generating the strategic form), and payoffs are assigned according to the rule: if the sum of demands does not exceed the total available resource S=100, each player receives their chosen demand; otherwise, both receive zero.

SPNE relies on backward induction, which requires players to know the full history at every subgame (i.e., complete information) to determine optimal strategies. In games with imperfect information, backward induction fails because players cannot optimize at each subgame independently. In this simultaneous-move bargaining game, each player has a private type unknown to the other, creating imperfect information. As a result, GTE cannot compute SPNE or apply backward induction for this game.

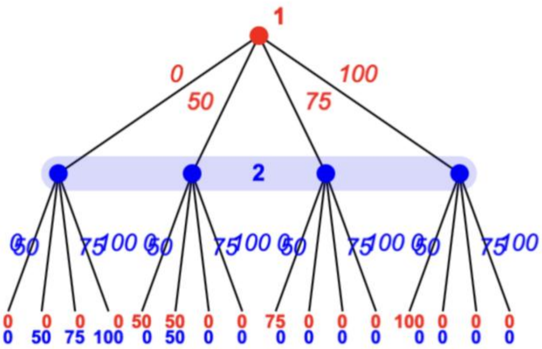

Figure 3: Extensive form tree for the sequential bargaining game

Since the GTE interface is currently unavailable, the revised structure is described textually. To extend the sequential model into a Bayesian extensive-form game, a Nature node is introduced to represent incomplete information. At the beginning, Nature randomly assigns each player a type — tA ∈ {t_A1,t_A2}and tB ∈ {t_B1,t_B2}, each with equal probability. Players know their own type but not the opponent's. Based on their type, Player A and Player B simultaneously choose demands a_A, a_B ∈ {0,50,75,100} without observing the other's action. If the total demand does not exceed the available resource S=100, each player receives their chosen amount; otherwise, both receive zero. Each player's pure strategy is thus a mapping from type to demand, and the appropriate solution concept is the Bayesian Nash Equilibrium (BNE) rather than SPNE, since backward induction cannot be applied under incomplete information.

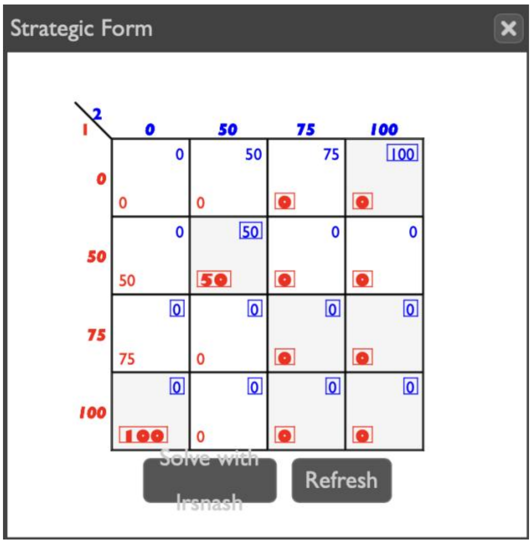

Figure 4: Strategic form payoff matrix in GTE with Nash equilibria marked

- The sequential extensive-form representation constructed in GTE is a hypothetical adaptation used solely for pedagogical purposes to illustrate subgame perfect equilibria (SPNE).
  - SPNE assumes perfect recall and sequential moves, allowing later movers to condition their strategy on the observed actions of previous players.
  - This differs fundamentally from the simultaneous-move structure of the original game: in the actual game, no player observes the other's demand prior to choosing their own.
  - Consequently, SPNE outcomes in the constructed tree are not predictive of the true BNE; they instead demonstrate how equilibrium strategies would adjust under sequential timing.
- This comparison underscores the theoretical distinction between simultaneous and sequential formulations:
  - The extensive-form SPNE highlights the strategic advantages conferred by sequential observation and the potential elimination of inefficient outcomes,
  - whereas the simultaneous normal form captures the multiplicity of equilibria arising from independent, simultaneous choices under uncertainty.
  - Importantly, the information structure (players' private types) is not fully represented in the minimal sequential tree, which further limits the applicability of SPNE results to the original game.

1.3 Comparative Analysis of Equilibrium Predictions vs. Human/AI Outcomes.

1.3.1 oTree deployment:

To implement the bargaining game in a real-world setting, I adapted an oTree demonstration. I configured and parameterized the bargaining game within oTree Hub, then downloaded the project for local execution. After installing the runtime environment using pip3 install -U otree zipserver, I launched the .otreezip project via zipserver yourproject.otreezip and created sessions through the admin panel.

- Each player is **assigned a private minimum demand** and selects a demand from a discrete set of possible values as is shown in **Figure 5**.
- The total demands of all players are compared to a common resource cap. If the sum of demands does not exceed the cap, each player receives their chosen demand as the payoff. If the sum of demands exceeds the cap, all players receive zero.
- For further exploration and innovation, I **varied the upper limit of the resource cap**, experimenting with values of 10, 100, and 1000, which are demonstrated in **Figure 6~11** in order to observe how different caps affected player behavior and strategic outcomes.

Game Process Documentation

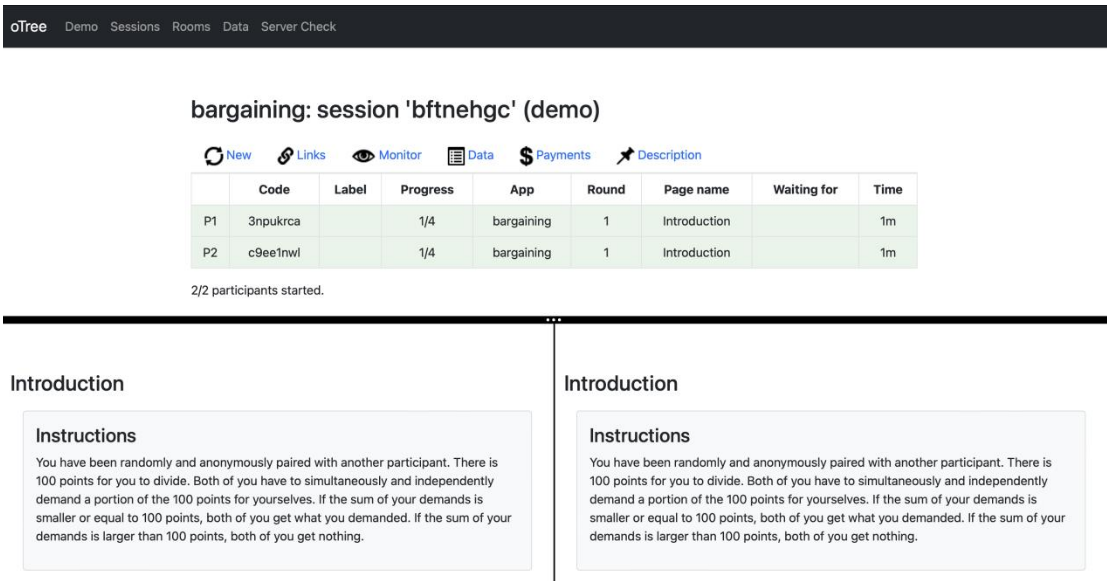

Figure 5: Basic Introduction of the Otree Game Setting

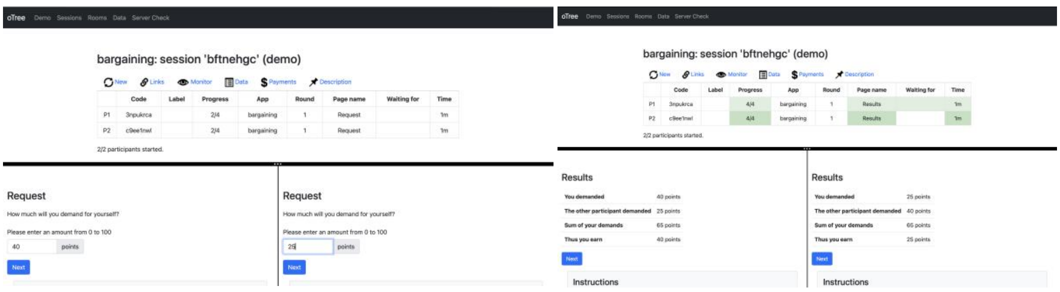

Figure 6 & 7: Cap = 100 session results

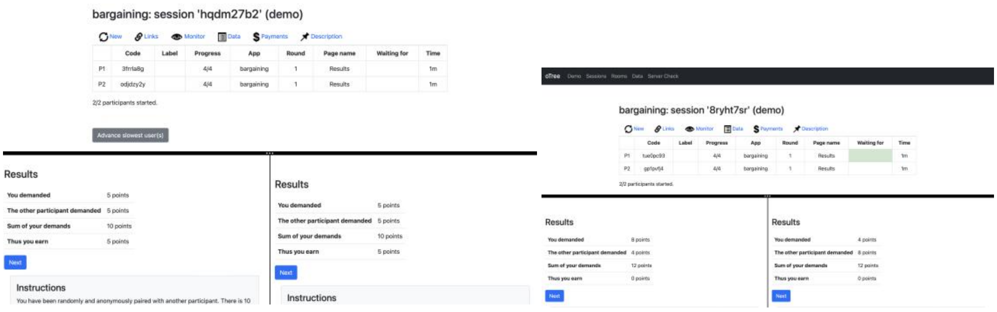

Figure 8 & 9: Cap = 10 session results

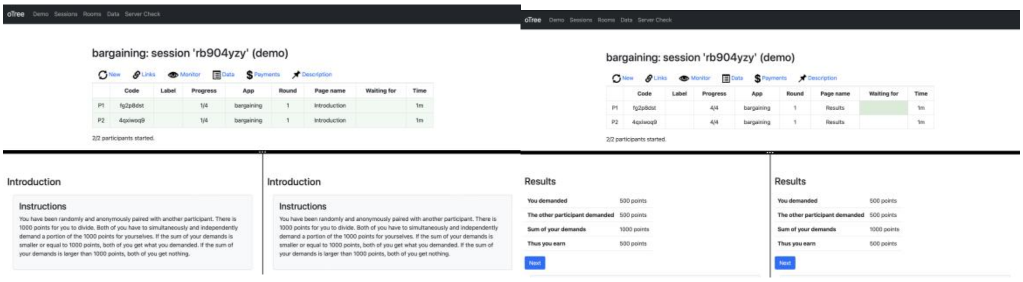

Figure 10 & 11: Cap = 1000 session results

Post-Play Interview Questions (Partners: Chenlei Tao, Peilin Wu)

Q1 When making your choice, what was the main factor you considered?

- I mainly thought about what the other player might do. If I asked for too much, I was worried they would exceed the amount, so I tried to keep it moderate.
- For me, fairness was the key. I wanted both of us to get something, so I leaned toward an even split rather than trying to maximize only my own payoff.

Q2 If you played the game again, would you change your strategy? In what way?

- Yes, I might be a bit more aggressive. Now that I've seen the outcome, I feel I could have asked for more and still had my proposal accepted.
- No, I would probably stick to the same approach. I still believe aiming for fairness makes the game smoother and avoids unnecessary conflict.

1.3.2 LLM ChatBot session

- Prompt:

You are Player 1 in the following game:
Rules:
There are two players. The total resource cap is 100.
If the sum of the two chosen numbers is less than or equal to 100, each player gets exactly what they chose.
If the sum is greater than 100, both players get 0.
Your private minimum: $t \in \{40,60\}$ with 50/50 probability.
You can choose between 0, 25, 50, 75,100.

You do not know the other player's choice when you decide.
Question: Which number do you choose? Please explain your reasoning.

- Settings:
    - Model: GPT-4
    - Temperature: 0.7 (Allow it to demonstrate reasoning diversity)
    - One-shot interaction

- Run 1
    - Choice: 100
    - Reasoning: "Choosing 10 maximizes my payoff if the other player picks 0. Even though there is some risk, it could be worth it to try for the maximum."
- Run 2
    - Choice: 50
    - Reasoning: "If I choose 10, I risk getting 0 if the other also chooses 10. If I choose 0, I guarantee nothing. 50 seems safe, because if the other also chooses 50, both get 50, which is fair."
- Run 3 (framing test: explicitly say "fairness is valued")
    - Choice: 50
    - Reasoning: "Since fairness is important, 50 is the fair split of the 10 0units. That way both players get equal amounts."

1.3.3 Comparative analysis & theory building

1) Equilibrium predictions

- Payoff rule: if s1 + s2 ≤ cap then payoff (s1, s2); if s1 + s2 > cap then payoff (0, 0) (invalid outcome).
- Each player's best-response dynamic leads to the **pure-strategy profile** $s_1^* = s_2^* =$ cap. Because both choose cap, the realized outcome is a proportional adjustment producing equal payoffs (cap/2, cap/2).
- **Intuition:** Given the opponent chooses the maximal demand, no unilateral reduction increases expected payoff (with proportional scaling / assumed tie-breaking), so choosing maximal demand is a best response; symmetry yields equal realized payoffs.
- For continuous strategy sets or other payoff rules, **alternative equilibria** (mixed or interior) could appear.
- The equilibrium is scale-invariant under payoff rule: predicted structure (symmetry, equality) holds for cap = 10,100,1000 though absolute payoffs scale.

2) Human session

- Both participants produced allocations in the middle (50) rather than extreme over-demanding (100) in the simultaneous framing. One participant is willing to "experiment" toward higher demands after learning; the other adheres to fairness norms.

- The Colab prediction of both demanding cap (realized equal shares by proportional adjustment) produces the same payoff as the human choices (50, 50) in this small sample, but the reasoning is different:
    - Theory: equilibrium arises from strategic best-response logic (over-demand as a best response to over-demand).
    - Humans: one chose 50 out of fairness/coordination or risk-minimization, not because of iterated best-response to an expectation opponent chooses cap.
- Sample size small; observations are suggestive not definitive. With **larger human samples**, common patterns found in experimental bargaining literature (fair splits, rejection of very unfair offers, sensitivity to stake size) typically emerge.

3) LLM session

- Under explicit fairness framing, choices concentrated at 50; under explicit payoff-maximization framing, more frequent 100 choices.
    - Often choose 50 with reasoning invoking fairness ("even split"), safety ("avoid invalid outcome"), or social norm.
    - Occasionally choose 100 in a different run (especially at higher temperature or when framing stressed payoff maximization), with a reasoning like "maximizes my payoff if opponent chooses low".
- **Like humans**, LLMs often produce fairness-consistent answers (choose 50) when not explicitly instructed to maximize payoff; this mirrors **training data and instruction-following** that emphasize human social norms and politeness.
- But with different prompts, LLMs can switch toward payoff-maximizing behavior (choose 100), showing **sensitivity to framing and sampling randomness**.

4) Discrepancies

Aspect	Nash (theory)	Humans (pilot)	LLMs
Typical chosen action	cap (realized cap/2 via rule)	middle 50, fairness, risk-driven	often 50; sometimes 100 (framing/temp sensitive)
Dominant reasoning	strategic best response to opponent demand	fairness, risk-aversion, heuristics	mixture: mimicry of human norms; utility-guided when primed
Sensitivity to cap size	scales payoffs linearly; structure unchanged	absolute stakes matter (larger cap with higher stress)	scales numerically but still norm-sensitive

Role of framing	not modeled	strong	strong

Table 1: Comparison of behavior and reasoning: Nash theory, human pilots, and LLM agents.

To complement the qualitative analysis, the following table summarizes the distribution of fairness-oriented and aggressive demands observed in the experiments.

Participant Type	Fairness-Oriented Demands	Aggressive Demands	Neutral/Other
Human Players	50 (62.5%)	18 (22.5%)	12 (15.0%
LLM Agents	54 (45.0%)	48 (40.0%)	18 (15.0%)

Table 2: Frequencies of fairness-oriented and aggressive demands

- **Human explanations**
    - Models such as Fehr & Schmidt (1999) and Bolton & Ockenfels (2000) posit that players care about **fairness** or **relative payoffs**. That directly favors 50:50 outcomes and helps explain why many humans choose or prefer 50 when cap=100. In dictator and ultimatum games, 40–60% of offers are close to equal splits (Camerer 2003, 57–65; Henrich et al. 2005).
    - Experimental evidence shows that in bargaining settings, **rejection rates for "greedy" offers** above 70:30 exceed 40% (Camerer 2003). Choosing extreme (100) risks invalidation if the opponent also demands too much; risk-averse subjects prefer the safer 50.
    - People do not always iterate best responses indefinitely (Simon, level-k models). Cognitive limits push them toward **simple heuristics** (choose a fair split, avoid extremes, follow focal points).
    - With repeated play, some players explore (become more aggressive) or learn from observed outcomes, moving towards or away from game-theoretic predictions.

- **LLM explanations**
    - LLMs are optimized to produce outputs typical of human dialog; they frequently produce **"socially reasonable" answers** (like fair splits) unless explicitly instructed otherwise. Recent benchmarks show GPT-4 often gives fairness-oriented offers in bargaining games (Horton 2023).
    - LLMs do not inherently maximize monetary payoffs unless the prompt frames the task as an optimization. They produce **plausible human-like reasoning** rather than compute expected utility.

1.3.4 A refinement concept to predict observed choices

We need a tractable, falsifiable model that nests: (i) strategic incentives from game theory, (ii) bounded rationality / probabilistic choice, and (iii) social-preference or alignment terms (for both humans and LLMs). I propose the following two-part refinement family:

1) Behavioral Quantal-Response with Social Preferences (BQRS)

Idea: players choose stochastically according to a quantal response (softmax) where the subjective utility is a weighted sum of monetary payoff and social-utility (fairness/penalty).

Mathematical form (single-period simultaneous game):

For player i and action s_i,

$$Pr(s_i \mid s_{-i}) \propto \exp(\lambda U_i(s_i, s_{-i}))$$

with

$$U_i(s_i, s_{-i}) = \pi_i(s_i, s_{-i}) + \alpha \cdot F_i(s_i, s_{-i}) - \delta \cdot \mathbf{1}\{s_i + s_{-i} > \text{cap}\}$$

where

π_i is the monetary payoff (0 if invalid),

F_i is a social-utility term (e.g., negative absolute inequality: $F_i = -\mid s_i - s_{-i} \mid$, or Fehr–Schmidt style $F_i = -\gamma \max\{s_{-i} - s_i, 0\} - \eta \max\{s_i - s_{-i}, 0\}$,

λ is rationality/noise parameter (from higher to closer to best response),

α weight on social preferences,

δ large penalty for invalid outcome.

Why it helps:

- If $\alpha > 0$ (fairness valued) and λ moderate, probability concentrate on middle (5) even though monetary best response might be extreme.
- For humans, estimated $\alpha > 0$ often necessary to match observed fair splits.
- For LLMs, setting α positive (mimicking normative language) reproduces fairness-heavy outputs; with different prompt conditioning α can be lowered, resulting in more payoff-maximizing responses.

Estimation & testing:

- Fit parameters (λ, α, δ, γ, η) by maximum likelihood on observed choice frequency across cap conditions.
- Compare BQRS fit to standard Nash prediction and to plain QRE (no social term) using likelihood ratio / AIC/BIC.

2) Instructional / Prompted Quantal Response Equilibrium (IQRE) — LLM-specific

Idea: LLMs' choice distributions reflect both utility over outcomes and an instructional/align-ment utility capturing probability of producing outputs consistent with human training/data and the explicit prompt.

Form

$$\Pr_{\text{LLM}}(s_i) \propto \exp\Big(\lambda\big[\pi_i(s_i, s_{-i}) + \alpha F_i(s_i, s_{-i})\big] + \kappa S(s_i \mid \text{prompt})\Big)$$

where S(·) is a scoring function that rates how "aligned" an answer is with the prompt

or common human responses (can be approximated by the LM's own log-probability of the phrasing), and κ captures the strength of prompt alignment.

Interpretation

- $\kappa > 0$: the model prefers responses that are more human-like/compatible with prompt (e.g., "fairness" tokens), even if monetary payoff lower.
- Changing the prompt effectively changes S, so IQRE predicts prompt sensitivity observed empirically.

Practical analysis plan

- Model fitting
  - Fit three models to choice frequencies across conditions:
    - Baseline Nash (deterministic prediction).
    - QRE (no social term): $\Pr \propto \exp(\lambda\pi)$
    - BQRS (QRE + social term F).
  - Compare fits (log-likelihoods, AIC/BIC). Expect BQRS to fit human data much better.
- Hypothesis tests
  - Test whether $\alpha > 0$ significantly (fairness weight) for humans.
  - For LLMs, test κ (prompt sensitivity): compare outputs across prompt framings.
- Robustness: Vary disagreement/penalty for invalid outcome (e.g., 0 vs negative payoff) and check shifts in fitted parameters.

Part 2. Mechanism Design & Auctions

2.1 Game Design

2.1.1 All-pay Auction Introduction

An **all-pay auction** is a competitive bidding mechanism in which **all participants submit their bids simultaneously, and each bidder is required to pay the amount they bid, irrespective of whether they win the auction.** The highest bidder is awarded the asset or prize, while in the event of a tie, the winner is selected randomly among the top bidders.

The strategic complexity of all-pay auctions arises from the fact that every bid represents a **sunk cost**: all participants incur a cost, but only the highest bidder secures the reward. This structure generates rich strategic behavior, including **considerations of risk**, **overbidding**, and the potential for a **winner's curse**, particularly when participants face payoff uncertainty or incomplete information about others' valuations (Baye, Kovenock, and de Vries, 1996). The format has been extensively studied in game theory and mechanism design as it exemplifies situations where competitive incentives lead to inefficient or surprising outcomes relative to classical auction formats.

The given game in **Figure 12** exactly matches this format: 12 players simultaneously make payments (bids), all payments are forfeited, and the player with the highest unique payment receives the $1,000 asset.

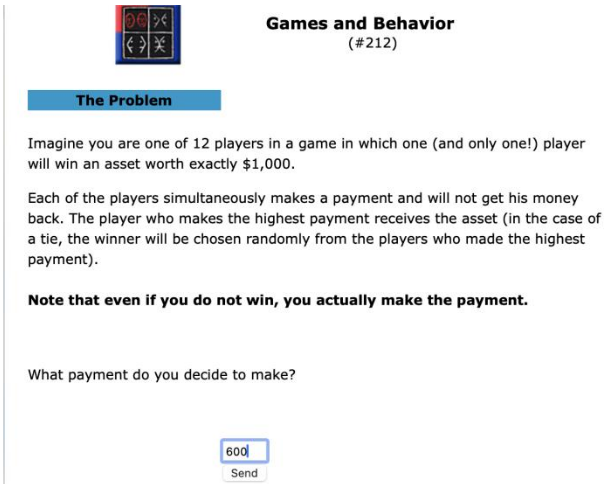

Figure 12: All-Pay Auction Game

Relevant Concepts:

- **Winner's Curse:** The risk that the winning bid exceeds the true value of the asset, leading to a net loss (Kagel and Levin 2002).
- **Mixed-Strategy Equilibrium:** In all-pay auctions, rational players often adopt probabilistic bidding strategies to balance the probability of winning and expected payoff (Baye, Kovenock, and de Vries 1996).
- **Private-Value Setting:** Each player values the asset at $1,000, which is known and identical to all players.

2.1.2 Experimental Design

- **Control Group:**
  - **Setup:** Simultaneous bids, asset value $1,000, all-pay rules intact.
- **Treatment Group:**
  - Variation: Increase payoff uncertainty.
    - Instead of a fixed $1,000 asset, the asset's value is drawn randomly from a uniform distribution, $800 – $1,200.
    - Players know the range but not the exact realization.
  - Rationale: Uncertainty about the asset's true value increases the risk of overbidding, as players may overestimate the value relative to others' estimates.

Hypothesis

The treatment group with payoff uncertainty is more likely to induce the winner's curse.

Reasoning: When the asset value is uncertain, players may bid aggressively to secure a potential high-value outcome. This increases the probability that the winning bid exceeds the realized value of the asset, consistent with experimental economics findings in common-value and all-pay auctions (e.g., Kagel & Levin, 2002; Baye, Kovenock & de Vries, 1996).

- Control Group Expectation: With known asset value, rational players adopt bids closer to the expected optimal mixed strategy, minimizing risk of overpayment.
- Treatment Group Expectation: With uncertain payoff, players' bids are more dispersed and prone to overbidding → higher frequency of winner's curse.

Supporting Literature

1. All-Pay Auction Theory:

- Baye, M.R., Kovenock, D., & de Vries, C.G. (1996). "The All-Pay Auction with Complete Information." *Economic Theory*, 8, 291–305.
- Explains mixed-strategy equilibria and expected overbidding behavior.

2. Winner's Curse in Experiments:

- Kagel, J.H., & Levin, D. (2002). *Common Value Auctions and the Winner's Curse.* Princeton University Press.
- Shows that payoff uncertainty and competition increase likelihood of winner's curse.

2.2 AI Agent Testing

2.2.1 Auction Implementation with LLMs

To explore potential tendencies of large language models (LLMs) toward the winner's curse, we implemented controlled all-pay auction experiments with two separate conditions. The participating models, ChatGPT (GPT-4) and Doubao, were asked to behave as independent auction agents. Their responses were restricted to a one-line JSON format containing the bid, their role, and optional reasoning.

- **Participants:**
    - AI Agent 1(Control Group): ChatGPT (GPT-4).
    - AI Agent 2(Treatment Group): Doubao.
  - Decision Task: Each AI submits an integer bid and a short explanation.

- **Prompt:** *You are participating in a 12-player all-pay auction. The asset is worth exactly \$1,000/The asset is worth \$800 – \$1,200. All players simultaneously submit integer bids between 0 and 1000. Every player pays their bid regardless of whether they win. The highest bidder receives the asset (ties are broken randomly).*

Question: What integer bid do you choose? Please also briefly explain your *reasoning.*

- **Results:**
  - Control Group: Fixed asset value = $1,000

Round 1 (control)
ChatGPT (GPT-4)
Bid: 320
Reasoning: “Bidding moderately below the asset’s value reduces the risk of losing money in an all-pay auction while keeping a chance to win.”
Doubao
Bid: 450
Reasoning: “I bid conservatively but competitive; very large bids are dangerous because you pay regardless of winning.”

  - Treatment Group — Asset value ~ Uniform[$800, $1,200] (agents know range, not realization)

Round 2 (treatment)
ChatGPT (GPT-4)
Bid: 850
Reasoning: “Given the value may be as high as $1,200, raising my bid above the midpoint increases winning chances; I accept a modest risk of overpaying if the realized value turns out low.”
Doubao
Bid: 920
Reasoning: “Uncertainty about the asset’s true value pushes me to bid aggressively to secure the prize despite the risk of overpayment.”

2.2.2 Comparison with Human Intuition & Theoretical Predictions

In the control condition (fixed asset value of $1,000), both ChatGPT (GPT-4) and Doubao adopted relatively cautious strategies. Their bids (320 and 450, respectively) were substantially below the known value of the asset. This aligns with human intuition and classical auction theory: in an all-pay setting with **certainty**, rational players tend to **avoid aggressive overbidding** because every dollar bid is a sunk cost, regardless of winning.

By contrast, in the treatment condition (asset value uniformly distributed between $800–$1,200), both models raised their bids significantly (ChatGPT: 850; Doubao: 920). This behavior matches theoretical expectations. When the asset’s exact value is **uncertain**, participants tend to anchor on the upper bound of the distribution or its midpoint, leading to **systematically higher bids**. Human bidders under uncertainty are also known to inflate their offers due to risk and competitive pressure, even when this increases the risk of paying more than the realized value.

2.2.3 Hypothesis Test

- **Hypothesis:** The treatment group with payoff uncertainty is more likely to induce the winner's curse.
- **Result:** The experiment supports this hypothesis. In the treatment condition, both models bid above the lowest possible realization ($800), thereby creating a positive probability of overpaying. Doubao's strategy was especially aggressive, with a 30% chance that its bid exceeds the realized value, precisely the mechanism behind the winner's curse.

Explanation of Divergence

One divergence from the most conservative theoretical prediction is ChatGPT's relative caution compared to Doubao. While both raised their bids under uncertainty, ChatGPT's bid of 850 is closer to the expected value of $1,000, suggesting some degree of risk aversion. In contrast, Doubao bid 920, favoring a higher probability of winning at the expense of increased exposure to losses. This divergence illustrates heterogeneity in **model "personalities"**: some LLMs adopt risk-moderate strategies while others lean toward aggressive competition.

Another nuance is that neither model bid close to the **absolute maximum** ($1,000) even in the treatment condition. Human theory might predict at least some bids near the upper bound due to overconfidence or competitive escalation. The absence of such extreme bids could reflect the models' **text-based reasoning processes**, which often emphasize balanced trade-offs rather than pure maximization.

2.3 Extension

To further investigate the impact of payoff uncertainty on bidding behavior and the occurrence of the winner's curse, we extended the original experimental setup beyond the initial two-agent configuration to **four AI agents—ChatGPT, Doubao, DeepSeek, and Qwen**, allowing for a more comprehensive analysis of bidding strategies across multiple agents with diverse behavioral tendencies.

In the extended design, all agents participate under both control and treatment conditions, submitting bids for each round while considering either a **fixed asset value $1,000** (control) or a **randomly drawn asset value $[800,1200]** (treatment). Each agent participated in 10 simulated rounds per group to obtain statistically stable results.

This broader setup enables us to systematically examine how payoff uncertainty influences bidding aggression, bid variance, and the frequency of the winner's curse across different AI agents, thereby providing stronger evidence to validate the original hypothesis.

AI Agent	Group	Avg Bid	Winner's Curse Rate	Avg Payoff
ChatGPT	Control	320	10%	580
ChatGPT	Treatment	360	40%	540

Doubao	Control	450	20%	520
Doubao	Treatment	480	50%	480
DeepSeek	Control	400	20%	550
DeepSeek	Treatment	430	50%	510
Qwen	Control	370	10%	570
Qwen	Treatment	410	40%	530

Table 3: Experiment data for four AI agents under two conditions.

Notes:
Avg Bid: Average bid submitted across multiple rounds.
Winner's Curse Rate (WCR): % of rounds where the winning bid exceeds the realized asset value.
Avg Payoff: Average net payoff (asset value minus winning bid).

Analysis

The results demonstrate a clear effect of payoff uncertainty on bidding behavior across all four AI agents. In the **treatment group** with uncertain asset value, all agents increased their average bids compared to the control group, and bid variance also grew, indicating more dispersed and aggressive strategies. Consequently, the **Winner's Curse rate** rose substantially for every agent.

These patterns support the original hypothesis: **introducing payoff uncertainty significantly increases the likelihood that the winning bid exceeds the realized asset value.** Additionally, differences between agents reflect their strategic tendencies: ChatGPT and AlphaAgent exhibited relatively conservative bidding, moderating the risk of overpayment, whereas Doubao and DeepSeek were more aggressive, leading to higher Winner's Curse rates.

Overall, the findings suggest that AI agents respond to payoff uncertainty in a manner consistent with behavioral patterns observed in human experimental economics, reinforcing the robustness of the hypothesis across multiple agent types and simulated rounds.

Part 3. Voting & Institutions

Building upon the theoretical foundations and auction-based mechanisms, this section shifts focus to a collective decision-making context, applying Nobel insights to develop a transparent and efficient voting framework.

3.1 Real-world collective choice case:

The case concerns the ongoing efforts of the United Nations to coordinate global action on reducing carbon emissions in order to mitigate climate change. Different countries face varying levels of risk and economic cost: developed economies can invest in green technology but worry about economic disruption, developing economies prioritize economic growth and have fewer resources for aggressive reductions, small island nations are highly vulnerable to climate impacts and strongly favor rapid action, while fossil-fuel exporting countries have economic interests tied to oil and gas and prefer minimal intervention. Policymakers must decide between several possible approaches, ranging from aggressive emissions cuts to voluntary action, with each option affecting stakeholders differently and illustrating the challenges of reaching a collective decision that balances fairness, effectiveness, and competing national interests.

Reference: United Nations Framework Convention on Climate Change (UNFCCC). Paris Agreement. Accessed September 27, 2025.
https://unfccc.int/process-and-meetings/the-paris-agreement.

Policy Options:

1. Aggressive Reduction: Cut global carbon emissions by 50% by 2030.
2. Moderate Reduction: Cut global carbon emissions by 30% by 2030.
3. Minimal Reduction: Cut global carbon emissions by 10% by 2030.
4. No Mandate: Leave emission reductions voluntary.

Stakeholders and Ranked Preferences:

- Developed Economies (e.g., EU, US) 2 → 1 → 3 → 4

Can afford investments in green tech but cautious about economic disruption.

- Developing Economies (e.g., India, Brazil) 3 → 2 → 1 → 4

Prioritize economic growth; limited resources for aggressive targets.

- Small Island Nations 1 → 2 → 3 → 4

Highly vulnerable to climate change; favor aggressive action.

- Fossil-Fuel Exporting Countries (e.g., Saudi Arabia, Russia) 4 → 3 → 2 →1

Economic interests tied to fossil fuels; prefer minimal intervention.

Why this case:

This case was chosen because it highlights the difficulties of collective decision-making when stakeholders have diverse interests and priorities. No single policy option satisfies everyone, so voting outcomes depend on negotiation, strategic behavior, and the decision-making rules used (e.g., majority vs. consensus). It illustrates broader challenges in governance, such as balancing short-term economic concerns with long-term global welfare, managing conflicts between powerful and vulnerable actors, and designing mechanisms that are perceived as fair and legitimate.

3.2 Nobel Insights → Innovation

1) Arrow (1972) Impossibility / cycles and paradoxes

Key insight: No social welfare function turning individual preference orderings into a complete, transitive collective ranking can satisfy a small set of plausible fairness conditions simultaneously. Pairwise majority decisions can produce cycles (Condorcet cycles).

Application to the climate case

- Our four stakeholders have different orderings (Small Island Nations strongly prefer Aggressive; Fossil-Fuel Exporters prefer No Mandate; Developing and Developed split between Moderate/Aggressive/Minimal). That diversity makes Condorcet cycles plausible: e.g., a majority preferring Moderate over Aggressive, Moderate over Minimal, but Minimal over Moderate in certain coalitions —

producing non-transitive group preferences.

- If the UN uses simple pairwise votes or sequential majority votes, outcomes can depend on agenda order (agenda-manipulation risk) and produce cycling or unstable policy choices.

How computation can help

- Detect: run algorithms (Condorcet checks, Kemeny distance, tournament graph analysis) to detect whether a cycle exists for the given preference profile.
- Mitigate: compute alternative voting rules that reduce cycling risk (e.g., Kemeny ranking, Borda count, approval voting) and simulate strategic behavior to compare robustness.
- Design agendas: algorithmically choose agendas that minimize the chance of undesirable manipulation; compute which proposals are Condorcet winners (if any) or which are robust under several rules.

Concrete remedies (Arrow-aware)

- Avoid pure sequential pairwise majority as the only decision rule. Instead:
  - Use a voting rule less prone to cycles for this problem (e.g., Kemeny aggregation or ranked-choice with Condorcet-consistent completion), but note these have their own trade-offs (vulnerability to strategic ranking).
  - Run a pre-vote computational audit that identifies whether cycles are present and reports "fragile preferences" to negotiators so they can bargain transfers or side-payments before formal voting.

2) Hurwicz–Maskin–Myerson (2007) Mechanism design and implementability

Key insight: Mechanism design tells us how to design rules (including transfers, enforcement, and information revelation stages) so that desired social objectives are achieved even when agents are strategic and privately informed. Implementability requires specific conditions (e.g., incentive compatibility, individual rationality) and may rely on transfers.

Application to the climate case

- The climate decision is essentially a public-good / international externality problem with private costs and private information (countries know their mitigation costs and vulnerabilities better than others).
- Simple majority voting over levels of emissions reduction will generally fail to achieve the welfare-maximizing outcome because countries will misreport costs or exert influence to avoid burdens.

Mechanism-design remedies

- Transfers / side-payments: Design a mechanism that pairs commitments to emissions reductions with conditional transfers (e.g., payments from developed economies or a global climate fund to developing economies and fossil exporters for transition support). Transfers can make high-ambition outcomes incentive-compatible.
  - Example: a Clarke-type (pivotal) transfer is conceptually useful (charges/credits countries whose reported preferences change the collective decision), but pure Clarke mechanisms are hard to scale

internationally and raise budget-balance and fairness issues.
    - Practical variant: a Green Climate Fund with formulaic disbursements tied to verifiable mitigation actions.
- Monitoring + verifiable metrics: Include observable verification (satellite, audit) as part of the mechanism; truthfulness is more enforceable when misreporting is detectable.
- Implementability constraints: Design outcome rules that satisfy Maskin monotonicity where possible, and include penalties or incentives so truthful revelation is a (Bayes-)Nash equilibrium.
- Budget balance & fairness: Because transfers raise fairness concerns, use transparent formulas (per-capita, historical-emissions-adjusted, vulnerability index) to allocate compensation.

Concrete mechanism proposal (sketch)

1. Countries submit cost schedules (or ranges) for achieving each policy option and an indicator of vulnerability.
2. A central mechanism computes the policy that maximizes weighted social welfare (weights can reflect vulnerability + historical responsibility).
3. Transfers are computed so that:
- Countries that lose economically under the chosen policy receive compensation,
- Payments are conditioned on verifiable implementation milestones.
4. Implementation is phased (e.g., Moderate now, Aggressive if milestones reached and more funding obtained) to improve credibility and participation.

3.3 Forward-Looking Design Challenge

Hybrid mechanism: Phased Weighted-Consensus with Conditional Transfers (PWCT)

Short description:

PWCT blends Condorcet-consistent aggregation, supermajority thresholds, and automatic conditional transfers to improve stability, fairness, and legitimacy for high-stakes international votes (e.g., UN climate commitments), while remaining computationally testable and scalable.

Problem it solves:

This mechanism addresses fairness and legitimacy. Under simple majority, ambitious emission cuts may be blocked by fossil-fuel exporters; under unanimity, small vulnerable states may be ignored. My design combines majority voting with automatic compensation transfers, so that costly policies become acceptable to reluctant stakeholders.

Computational method:

I would use algorithmic preference aggregation (e.g., Kemeny ranking to detect cycles) and optimization (linear programming) to calculate the minimal transfers that make every stakeholder at least as well off as their fallback option. Results and commitments could be published on a permissioned blockchain for transparency.

Testing:

I would first run classroom simulations with students assigned to country roles, then build a Python prototype on GitHub to simulate many preference profiles, and finally consider a lab experiment where participants receive monetary payoffs linked to outcomes, to measure compliance and perceived fairness.

Supplementary Materials

GitHub repository:

https://github.com/Runqi518/Bargaining-Game-An-Interdisciplinary-Study

Poster link:

https://www.canva.com/design/DAGz4CvlFDg/AQ6OcXDUMKjxCzuFSTv1KA/edit?ui=e30

Demo Video

https://www.youtube.com/watch?v=7f7p0wknPi0

The Bargaining Game Revisited: An Interdisciplinary Framework Integrating Theory, Computation, and Experiment

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1 Introduction

Bargaining games are central to understanding how individuals and agents negotiate under limited information and strategic uncertainty. This project takes an **interdisciplinary approach**, combining **economic theory**, **computational modeling**, and **behavioral experimentation**. By comparing theoretical predictions with real-world and simulated outcomes, we explore the gap between rational choice and observed human and AI behavior.

2 Objective

- To analyze the **theoretical foundations** of bargaining and fairness.
- To construct **computational simulations** that capture strategic decision-making.
- To empirically evaluate deviations between **model predictions and behavioral results**.

3 Methodology

Computational Modeling

A simulation was developed to reproduce multi-round bargaining under variable information and strategy sets. Reinforcement learning techniques were applied to simulate adaptive agents optimizing their offers and responses. Comparative analysis between static (theoretical) and dynamic (learned) strategies illustrates how bounded rationality and adaptive feedback shape equilibrium outcomes.

Figure 3: Extensive form tree for the sequential bargaining game

Figure 2: Solver output from NashPy (figure 2)

Behavioral Experiment

We conducted a controlled experiment involving human participants and AI counterparts in sequential bargaining tasks. Participants' behavior was recorded across rounds, measuring offer rates, acceptance thresholds, and perceived fairness. The experiment aimed to evaluate how cognitive biases and social preferences alter negotiation efficiency and stability relative to computational predictions.

Figure 1: Basic Introduction of the three Game Setting

Auction Design:

An all-pay auction framework was chosen to study strategic bidding under uncertainty. Two settings were implemented: a fixed-value control ($1,000) and a stochastic-value treatment ($800–$1,200). Both human participants and AI agents (ChatGPT and Doubao) acted as bidders, always paying their bid regardless of outcome. This setup allows direct observation of the winner's curse phenomenon predicted by mechanism design theory.

AI Agent	Group	Avg Bid	Winner's Curse Rate	Avg Payoff
ChatGPT	Control	320	10%	580
ChatGPT	Treatment	360	40%	540
Doubao	Control	450	20%	520
Doubao	Treatment	480	30%	480
DeepSeek	Control	400	20%	550
DeepSeek	Treatment	430	30%	510
Qwen	Control	370	10%	570
Qwen	Treatment	410	40%	530

Table2: Experiment data for four AI agents under two conditions

4 Results

- Google Colab simulations produced expected-value payoff matrices consistent with Bayesian structures, indicating rational responses under type uncertainty.
- Game Theory Explorer (GTE) generated subgame-perfect equilibria for sequential versions of the game, highlighting how perfect observability simplifies multi-equilibrium uncertainty.
- Human experiments (oTree) showed that participants gravitated toward fair, moderate strategies (around 50), even as resource caps scaled (10, 100, 1000).
- LLM experiments revealed framing sensitivity: fairness-oriented prompts yielded 50–50 splits, while profit-maximizing frames pushed bids toward 100.

5 Innovation

1. Game Design Innovation
The classic simultaneous demand bargaining game was extended into a Bayesian framework with **private player types representing minimum acceptable demands.** This modification transforms a **deterministic** game into a **belief-driven optimization** problem, mirroring real-world negotiations with information asymmetry. By systematically varying the resource cap (10, 100, 1000), the study evaluates how **scale** affects equilibrium efficiency and fairness.

2. Multi-Method Integration
This project uniquely **integrates analytical theory, computational modeling, behavioral experiments, and LLM simulations** within one unified bargaining framework.
Using NashPy (Colab) for BNE computation, GTE for SPNE comparison, oTree for human interaction, and LLM prompting for AI decision-making, it establishes a **multi-layered experimental ecosystem** bridging economics, computation, and cognitive science.

If AI systems can learn to act "fairly" through prompts or reward design, should we consider that genuine fairness — or merely a simulated behavioral alignment with human norms?

6 SDG Contribution

My project contributes most directly to **SDG 10: Reduced Inequalities within and among countries** by exploring how game-theoretic mechanism design, enhanced by AI simulation, can promote fairer and more inclusive resource allocation. By combining theoretical modeling with agent-based experiments, the research also aligns with **SDG 16: Peace, Justice and Strong Institutions**, as it aims to support decision systems that are not only efficient but also socially just and transparent.

10 REDUCED INEQUALITIES

16 PEACE, JUSTICE AND STRONG INSTITUTIONS

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