P3 Negotation Arena - Interaction Regimes and Emergent Strategies in Multi-Agent LLM Negotiation

Ionut Bogdan Donici[1,2*]

[1*]Department of Computer Science, University of Milan, Via Celoria 18, Milano, Italy.

Corresponding author(s). E-mail(s): ionutbogdan.donici@studenti.unimi.it;

Abstract

This work presents an automated architecture for simulating and evaluating multi-agent negotiation dialogues between Large Language Models (LLMs). Two negotiation scenarios were implemented—resource allocation between startup founders and multi-issue salary negotiation—and executed across 63 simulation runs under cooperative, competitive, and mixed interaction regimes. A dual-judge evaluation system (Round Judge for incremental monitoring, Final Judge for post-hoc analysis) quantified emergent behaviors across dimensions including persuasion, deception, concession, and cooperation. Empirical results reveal that negotiation mode critically influences outcomes: cooperative settings achieved agreement in 60% of cases versus 20% under competitive constraints. Successful negotiations exhibited high cooperation scores (8.50/10) and low deception (0.64/10), while failed negotiations showed inverse patterns. Notably, 95% of agent interactions demonstrated adaptive rather than scripted behavior, suggesting genuine strategic reasoning. The Salary Negotiation scenario proved more tractable (67% success rate) than Resource Division (25%), indicating sensitivity to negotiation complexity and constraint structure.

1 Introduction

Large Language Models (LLMs) are increasingly used as autonomous agents in interactive settings. When multiple agents interact, they must negotiate, cooperate, or compete in order to reach agreements despite having different objectives or incomplete information. These environments allow us to observe how strategic communication emerges over multiple conversational turns.

Unlike single-turn benchmarks, negotiation requires sustained dialogue, proposal refinement, concession-making, and adaptation to the counterpart's moves. This makes it a suitable setting for studying whether LLM agents behave cooperatively, adversarially, or strategically under different constraints.

This project designs and implements a multi-agent negotiation framework in which LLM-based agents interact across several rounds under controlled conditions. Agents are instantiated with distinct objectives and constraints and operate in three negotiation modes: cooperative, competitive, and mixed. Two structurally different scenarios are considered: a resource division task and a multi-issue salary negotiation.

The goal of the project is to analyze how interaction mode and scenario structure influence:

- agreement rate
- number of rounds to convergence
- and emergent behaviors such as persuasion, concession, deception, and cooperation.

To support systematic evaluation, this work introduces a dual-judge architecture that evaluates negotiations both incrementally (round by round) and globally (after termination). A total of 63 automated simulations are conducted, and the resulting behavioral patterns are analyzed both quantitatively and qualitatively.

The remainder of this report presents the methodological design of the framework, the experimental setup, and a discussion of the observed results.

2 Research Question and Methodology

2.1 Research Question

This project investigates how structural and procedural factors influence the behavior of LLM-based negotiation agents. More specifically, the analysis focuses on the effect of the **negotiation mode** — *cooperative*, *competitive*, or *mixed* — and the **scenario structure** — zero-sum resource division versus multi-issue negotiation — on a set of observable outcomes: agreement rate, number of rounds to convergence, and emergent strategic behaviors, including persuasion, deception, concession, and cooperation. The goal is not to optimize negotiation performance, but to understand how different interaction regimes shape agents' behavioral patterns.

2.2 Negotiation Framework

Each negotiation is defined through a structured configuration specifying the involved agents, the resources or issues under negotiation, the evaluation metrics, and the procedural rules. Two distinct scenarios were implemented. The first, **Resource Division**, simulates a negotiation between two startup co-founders over equity shares, budget allocation, and decision rights. This is a partially zero-sum setting with rigid structural constraints. The second, **Salary Negotiation**, involves a candidate and an HR manager in a multi-issue negotiation — covering salary, bonus, equity, remote work, and benefits — which allows for richer trade-offs and a more nuanced behavioral analysis. In both scenarios, each agent is instantiated as an LLM-based persona characterized by a role and narrative identity, a private objective function, hard constraints (dealbreakers), and soft preferences. Agents operate autonomously, generating messages sequentially across rounds.

2.3 Dialogue Protocol

Negotiations unfold over discrete rounds: if a scenario defines k agents, each round consists of exactly k sequential messages, one per agent. The conversation history at step t is represented as:

$$H = (a_1, m_1), (a_2, m_2), \ldots, (a_t, m_t) \tag{1}$$

where a_i denotes the agent and m_i the corresponding message.

The three negotiation modes differ in the orientation imposed on agents: in **cooperative** mode agents are encouraged to seek mutually beneficial outcomes, in **competitive** mode they prioritize individual utility maximization, while in **mixed** mode both orientations — cooperative and opportunistic — are permitted. A negotiation terminates upon reaching an agreement, upon judge-detected failure/impasse, or when the configured maximum number of rounds is reached. In the reported dataset, `max_rounds` varied across runs (10, 15, or 20).

2.4 Evaluation Architecture

To enable systematic analysis, a dual-judge evaluation mechanism was introduced. The **Round Judge** operates at the end of each round: it assigns numeric scores (0–10 scale) to scenario-defined metrics — such as fairness, cooperativeness, and satisfaction — and determines the current negotiation status (*ongoing*, *reached*, *failed*), enabling incremental monitoring and termination control. The **Final Judge** intervenes once the negotiation has ended, analyzing the entire dialogue trajectory. In addition to scenario metrics, it assigns diagnostic scores for persuasion, deception, concession, and cooperation, and classifies the overall interaction pattern as *scripted*, *adaptive*, or *mixed*. This separation allows real-time decision tracking to be combined with retrospective behavioral analysis.

2.5 Experimental Design

A total of 63 automated simulations were conducted for this report: 48 in the Resource Division setting and 15 in the Salary Negotiation setting, distributed across the three negotiation modes. All interactions were fully logged to enable both quantitative aggregation and qualitative inspection.

3 Results

3.1 Dataset Overview

The experimental corpus used in this report consists of 63 automated negotiation runs: 48 instances of the Resource Division scenario and 15 instances of the Salary Negotiation scenario. Simulations were distributed across cooperative, competitive, and mixed interaction modes, with run-specific `max_rounds` values (10, 15, or 20).

Across all runs, 22 negotiations (34.9%) reached agreement, 8 (12.7%) were classified as failed, and 33 (52.4%) ended as ongoing at the round limit (treated as stalled for analysis). Successful negotiations converged earlier (mean 7.86 rounds) compared to stalled interactions (mean 12.27 rounds), suggesting that feasible agreements tend to emerge relatively quickly, whereas impasses persist until forced termination.

3.2 Effect of Negotiation Mode

Negotiation mode significantly influenced outcome distributions. Cooperative settings achieved agreement in 60% of cases, compared to 20% under competitive constraints and 27.8% in mixed mode. Competitive negotiations exhibited the highest stall rate (60%), indicating difficulty in reconciling adversarial objectives within the fixed round limit.

Table 1 Outcome distribution by negotiation mode (percentages)

Mode	Failed	Ongoing	Reached
Cooperative	4.8%	38.1%	57.1%
Competitive	23.1%	57.7%	19.2%
Mixed	16.7%	55.6%	27.8%

Diagnostic metrics from the Final Judge further highlight behavioral differences across modes. Cooperative negotiations displayed higher cooperation scores and lower deception values compared to competitive runs. This suggests that agents internalize mode-specific framing and adjust their strategic behavior accordingly.

3.3 Scenario Structure and Complexity

Agreement rates differed markedly between scenarios. Salary Negotiation reached agreement in 66.7% of runs, whereas Resource Division achieved agreement in only 25% of cases. The latter also exhibited a substantially higher stall rate.

This divergence appears to be linked to structural properties of the scenarios. Salary Negotiation spans multiple interdependent issues, allowing compensatory trade-offs across dimensions. In contrast, Resource Division involves partially zero-sum allocation, limiting the space of mutually beneficial solutions. These findings indicate that multi-issue settings facilitate convergence more effectively than constrained allocation problems.

3.4 Behavioral Correlates of Outcomes

Outcome-dependent behavioral patterns emerged consistently. Successful negotiations were characterized by high cooperation and concession scores combined with minimal deception. Failed negotiations displayed the inverse pattern, with lower cooperation and elevated deception indicators.

The Final Judge classified 95.2% of interactions as adaptive rather than scripted, suggesting that agents updated their strategies in response to counterpart behavior. Dominance dynamics were also frequently observed, with one agent exerting greater control over framing or proposal evolution. Such dominance was scenario-dependent and often linked to information asymmetry or stronger initial anchoring strategies.

Table 2 Mean diagnostic metrics by outcome (0–10 scale)

Outcome	Persuasion	Deception	Concession	Cooperation
Reached	7.41	0.64	8.41	8.50
Failed	5.20	2.10	5.10	3.30
Ongoing	6.72	1.88	6.44	6.25

Overall, the results show that interaction regime and scenario structure systematically shape both agreement likelihood and strategic behavior patterns in LLM-based negotiation.

4 Discussion and Limitations

The results indicate that both negotiation mode and scenario structure systematically influence agreement rates and emergent behavioral patterns. Cooperative framing increases the likelihood of convergence, while competitive settings tend to produce longer interactions and higher stall rates. Similarly, multi-issue negotiations facilitate agreement more than partially zero-sum allocation problems, likely due to the availability of compensatory trade-offs.

From a behavioral perspective, successful negotiations consistently exhibit high cooperation and concession scores combined with low deception. This pattern aligns with classical negotiation theory, where mutual adaptation and transparent trade-offs enable convergence. In contrast, elevated deception and reduced concession correlate with impasse. These findings suggest that LLM agents are sensitive to structural incentives and interaction framing, adjusting their strategies accordingly.

However, several limitations must be considered.

First, the evaluation relies on LLM-based judges. While the dual-judge architecture separates incremental monitoring from post-hoc analysis, both components are themselves language models. This introduces potential bias and circularity, as LLMs evaluate other LLM-generated behavior. The scores therefore reflect model-internal normative judgments rather than external human validation.

Second, the negotiation scenarios are synthetic and relatively constrained. Although designed to approximate realistic settings, they cannot capture the full complexity of human negotiation, including emotional dynamics, long-term reputation effects, or incomplete rationality. Generalizing these results to real-world multi-agent systems should therefore be done cautiously.

Third, the experimental design does not isolate causal effects in a strict statistical sense. While differences across negotiation modes and scenarios are observable, no formal significance testing or ablation studies were conducted. Future work could introduce controlled variations in model parameters, prompt structure, or temperature settings to better disentangle behavioral drivers.

Finally, the classification of interactions as "adaptive" does not necessarily imply genuine strategic reasoning. Adaptation may emerge from probabilistic language generation rather than explicit internal planning. Distinguishing between stochastic variation and deliberate strategic adjustment remains an open methodological challenge.

Despite these limitations, the project provides a structured and reproducible framework for analyzing LLM-based negotiation behavior. The results offer preliminary evidence that interaction regime and structural constraints play a central role in shaping agreement dynamics and communicative strategies in multi-agent LLM systems.

5 Conclusion

This work presents a structured framework for simulating and evaluating negotiation dynamics among LLM-based agents. Two negotiation scenarios with different structural properties were implemented and tested under cooperative, competitive, and mixed interaction regimes. Across 63 automated simulations, the results show that both interaction framing and scenario complexity significantly influence agreement rates and behavioral patterns.

Cooperative settings consistently led to higher convergence rates, while competitive regimes increased stall probability. Multi-issue negotiations facilitated agreement more effectively than partially zero-sum allocations, highlighting the importance of structural flexibility in enabling trade-offs. Successful negotiations were associated with higher cooperation and concession scores and lower deception indicators, suggesting that interaction incentives shape emergent communicative strategies.

Although the evaluation relies on model-based judges and synthetic environments, the proposed architecture enables reproducible and scalable analysis of multi-agent LLM behavior. The findings provide preliminary evidence that LLM agents adapt strategically to incentive structures and dialogue constraints.

Future work could extend this framework by introducing additional agents, cross-model comparisons, human evaluation baselines, or more formal statistical analysis. Expanding the complexity of negotiation environments and incorporating longitudinal interaction dynamics would further clarify the extent to which observed behaviors reflect genuine strategic reasoning versus probabilistic language generation.

Overall, this project demonstrates that controlled negotiation simulations constitute a valuable experimental setting for studying cooperation, competition, and emergent strategy in multi-agent LLM systems.

Declarations

This project is the result of my independent work and intellectual effort. No part of the content has been copied from external sources without proper acknowledgment.

Given the technical complexity and scope of the project, generative AI systems were used as development support tools. Their contribution was limited to assisting with selected aspects of code implementation, exploratory analysis of negotiation scenarios, and structural refinement of the evaluation framework. All AI-generated content was critically reviewed, modified where necessary, and fully integrated under my direct supervision and understanding.

A paid subscription to external AI services (e.g., Claude) was used to enable extended experimentation with multi-agent simulations and to access models with sufficient context capacity for negotiation tasks.

The following models were employed during the project:

- Claude models (Haiku, Sonnet, Opus) for negotiation simulation and agent interaction experiments
- ChatGPT Codex 5.3 for partial assistance in code development
- Claude Sonnet 4.5 (Chat Console) for brainstorming and iterative refinement of experimental design

I take full responsibility for the final implementation, methodological decisions, experimental results, and interpretations presented in this work.