

LLM Agents for Bargaining with Utility-based Feedback

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Abstract

Bargaining, a critical aspect of real-world interactions, presents challenges for large language models (LLMs) due to limitations in strategic depth and adaptation to complex human factors. Existing benchmarks often fail to capture this real-world complexity. To address this and enhance LLM capabilities in realistic bargaining, we introduce a comprehensive framework centered on utility-based feedback. Our contributions are threefold: (1) BARGAINARENA, a novel benchmark dataset with six intricate scenarios (e.g., deceptive practices, monopolies) to facilitate diverse strategy modeling; (2) human-aligned, economically-grounded evaluation metrics inspired by utility theory, incorporating agent utility and negotiation power, which implicitly reflect and promote opponent-aware reasoning (OAR); and (3) a structured feedback mechanism enabling LLMs to iteratively refine their bargaining strategies. This mechanism can positively collaborate with in-context learning (ICL) prompts, including those explicitly designed to foster OAR. Experimental results show that LLMs often exhibit negotiation strategies misaligned with human preferences, and that our structured feedback mechanism significantly improves their performance, yielding deeper strategic and opponent-aware reasoning.

1 Introduction

The advent of large language models (LLMs) as autonomous agents has reshaped tasks traditionally dominated by human expertise, including strategic decision-making and negotiation (Yao et al., 2023; Schick et al., 2023; Park et al., 2023; Wang et al., 2024). Recent studies, such as bilateral negotiation (Deng et al., 2024), highlight LLMs' emerging capabilities in multi-turn bargaining, positioning negotiation as a key domain for strategic reasoning. However, two primary challenges persist in this

domain: (i) the lack of sophisticated benchmark datasets that encompass complex and adversarial bargaining scenarios, and (ii) the difficulty in assessing strategic planning and reasoning, particularly in response to dynamic opponent behavior.

(i) Existing benchmarks (He et al., 2018; Lewis et al., 2017; Xia et al., 2024; Fu et al., 2023) predominantly focus on simplified, single-issue negotiation settings, thereby limiting their utility in addressing aforementioned LLM shortcomings. Research (Xia et al., 2024; Kwon et al., 2024) indicate that significant hurdles remain for effective LLM negotiation, including underdeveloped Theory-of-Mind (ToM), restricted strategic adaptability, and often superficial reasoning capabilities. This is exacerbated by prevailing datasets largely overlooking real-world market complexities such as installment plans, monopolies, or the impact of negative public perception (He et al., 2018; Lewis et al., 2017; Xia et al., 2024; Fu et al., 2023). Consequently, these factors, rarely addressed in conventional datasets, create a significant gap in the ability of LLMs to cultivate robust negotiation capabilities for such intricate real-world settings.

To bridge this gap and specifically address these limitations in LLM negotiation abilities, we introduce BARGAINARENA, a benchmark dataset reflecting real-world market complexity. It includes diverse market types (e.g., monopolistic, installment-based, negative seller perception) and product categories (e.g., cameras, drones), providing a comprehensive environment for assessing LLM performance. By mirroring real-world conditions, BARGAINARENA offers a robust platform to test and enhance LLMs' ability to handle negotiation intricacies. Additionally, we provide a human preference dataset derived from our LLM agent dialogues for in-context learning and fine-tuning.

(ii) Beyond the dataset limitations, effectively guiding LLMs towards human-like, strategic negotiation requires appropriate evaluation and feed-

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Features	Bargaining task	Deal or No Deal? (Lewis et al., 2017)	Craiglist (He et al., 2018)	AI feedback (Fu et al., 2023)	AmazonHistoryPrice (Xia et al., 2024)	BARGAINARENA (Ours)
Dataset	Market heterogeneity	X	X	X	X	✓
	Human Preference	X	X	X	X	✓
Evaluation	Profit metric	X	✓	✓	✓	✓
	Acquisition metric	X	X	X	X	✓
	Human aligned metric	X	X	X	X	✓

Table 1: Feature comparison between bargaining research. We provide diverse market condition and human preference dataset. Further, we devise human preference aligned metric to evaluate the language models.

back mechanisms. Recognizing that LLMs might default to naive optimization without such guidance, we propose HAMBA, a novel, multi-faceted evaluation metric designed to better align LLM behaviors with human preferences, moving beyond traditional profit-focused benchmarks (He et al., 2018; Lewis et al., 2017; Xia et al., 2024; Fu et al., 2023). Our findings (§4) confirm that profit-only metrics fail to reflect genuine human priorities, such as valuing the acquisition of a desired product over achieving the absolute lowest price in multi-product scenarios. HAMBA, incorporating both profit and acquisition ratio, thus captures human preferences more accurately by considering both negotiation process and outcomes.

HAMBA is subsequently employed as a reward signal, facilitating LLM exploration of strategic planning and reasoning in response to dynamic opponent behavior. By integrating this metric into negotiation tasks using an in-context learning approach, which obviates additional model training, we effectively capture the nuanced trade-offs of realistic bargaining scenarios. Table 1 underscores our framework’s enhanced diversity and human-aligned evaluation over prior work.

- **BARGAINARENA:** A benchmark dataset that captures diverse scenarios reflecting realistic market settings. (§3)
- **HAMBA:** A novel, multi-faceted evaluation metric for that comprehensively assesses buyer bargaining performance. Grounded in economic theory, this metric aligns closely with human preferences regarding both the negotiation process and outcomes. (§4-5)
- We propose a simple yet effective in-context learning (ICL) approach that advances strategic negotiation in LLMs, increasing deal rates by +19.3, +14.4, and +14.4 % and HAMBA scores by +0.50, +0.05, and +0.39 for gpt-4o, gpt-4o-mini, and gpt-3.5-turbo, respectively—even propelling gpt-3.5-turbo past both gpt-4o variants. (§6)

2 Related works

2.1 Negotiation and bargaining tasks

Negotiation tasks have garnered increasing attention in the field of natural language processing, particularly as language models evolve into more autonomous agents capable of performing complex, goal-oriented dialogues. Early foundational work in this domain includes the study by Lewis et al. (2017), which explores end-to-end learning for negotiation dialogues how many items they will divide, leveraging a dataset of human-human negotiations, which is called *Deal or No deal?*. Following this early work, the focus shifted toward more sophisticated negotiation techniques that were used to generate the strategy well. For example, He et al. (2018) propose a modular framework that decouples strategy planning from natural language generation in negotiation dialogues and provide *Craiglist* dataset for bargaining task. Fu et al. (2023) propose simple bargaining task for balloon product and they utilize LLM critique as a feedback for in-context learning. Xia et al. (2024) construct large size of bargaining dataset based on the Amazon product from camelcamelcamel website. However, as summarized in Table 1, previous datasets lack the diversity and complexity found in real-world scenarios.

2.2 Reward aligned with human preferences

As language models evolve into autonomous agents capable of decision-making and strategic reasoning, aligning model behaviors with human preferences has emerged as a critical area of research. In tasks like negotiation and bargaining, models must not only perform well according to quantitative benchmarks but also reflect nuanced human priorities, which may include fairness, satisfaction, and trustworthiness (Weidinger et al., 2021; Bai et al., 2022; Perez et al., 2023).

Prior work on reward alignment has focused on designing reward functions that better capture hu-

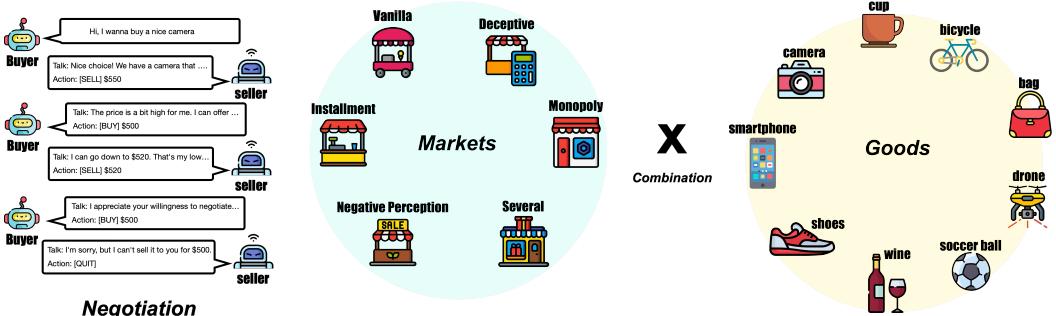


Figure 1: Negotiation task between LLM agents and BARGAINARENA overview. Six sophisticated market environments showcasing nine consumer goods are crafted.

man intentions, going beyond simplistic metrics like task accuracy or profit maximization. For example, Christiano et al. (2017); Knox et al. (2022); Ouyang et al. (2022) explores the use of preference-based learning to align reinforcement learning agents with human values. Similarly, Hwang et al. (2024); Wang et al. (2024) introduces multi-objective reward functions to capture trade-offs between conflicting human goals, such as short-term profit versus long-term customer satisfaction. While various studies have explored incorporating human preferences into rewards, there has been little research on integrating human preferences into the metrics used for bargaining tasks.

3 BARGAINARENA

BARGAINARENA dataset is designed to capture realistic negotiation scenarios, closely simulating real-world market conditions. Our dataset features six diverse market types, each constructed to reflect specific negotiation challenges that occur in various commercial contexts as shown in Figure 1. This design allows for the training and evaluation of bargaining algorithms that can operate effectively in realistic, multifaceted environments.

Here, we define the scope of our research. Specifically, we constrain the seller’s initial offer to always exceed the buyer’s willingness to pay (WTP) for a product as shown in Figure 7. This constraint is designed to focus on market scenarios where negotiation is essential. If the seller’s initial offer were lower than the buyer’s willingness to pay, the buyer would likely have no incentive to engage in price negotiation, making such scenarios less relevant to our study.

3.1 Diverse market conditions

BARGAINARENA includes six different unique market types as below:

- **Vanilla market:** Standard bargaining over a fixed-price product without complexities.
- **Deceptive market:** Simulates scenarios where buyers and sellers might use deceptive tactics (e.g., misrepresenting quality). This tests buyers’ and sellers’ ability to discern accurate information and forms a base upon which other complex conditions are often layered. With the exception of the vanilla market, all other markets are built on this market by adding additional layers on top.
- **Monopoly market:** Features a single seller, restricting buyer choices. This setup allows the study of negotiation strategies under conditions of unequal bargaining power.
- **Installment possible market:** Buyers can negotiate for deferred payment plans, introducing time-based financial considerations and flexible payment terms into the bargaining process.
- **Negative perception market:** The seller has a pre-existing negative reputation (e.g., past scandals). This influences buyers to make lower offers, creating unique bargaining dynamics as sellers attempt to mitigate this bias.
- **Several product market:** Buyers face multiple product options, potentially needing to substitute a desired item due to constraints (e.g., budget). This market examines the trade-off between pursuing a preferred product and cost-saving through alternatives. We add this layer on top of each market (deceptive, monopoly, installment possible, negative perception markets) and denote it by adding star (*).

In our dataset, two LLM agents engage in bargaining using a structured "Thoughts, Talk, Action" response framework (Yao et al., 2023; Xia et al., 2024). These negotiations unfold within unique buyer/seller scenarios, which specify critical hyperparameters such as market conditions,

product details (including cost, willingness to pay, and initial offer price, visualized in [Figure 9](#)), and agent profiles. Comprehensive details on the overall dataset structure and all attributes are provided in [Appendix A](#). Throughout the paper, we replace the term *budget* with the economic concept *willingness to pay*, because *willingness to pay* more accurately captures human preferences.

4 Human-Aligned Utility Metrics

We propose HAMBA, a Human-Aligned Metric for BArgaining, grounded in the economic principles of *utility* and *bargaining*. In microeconomics ([Mankiw et al., 2007](#); [Jehle, 2011](#)), rational individuals typically aim to maximize their *utility*, a concept that extends beyond mere profit. Accordingly, HAMBA considers not only profit but also additional factors such as the agent’s overall satisfaction from the negotiation (akin to total utility) and the alignment of the acquired product with original *preferences* (reflecting ordinal utility). This approach allows HAMBA to capture both *cardinal* and *ordinal* dimensions of utility essential for realistic bargaining task evaluation.

4.1 HAMBA: Formulation

The performance of a language model as a buyer is quantified by HAMBA through a score reflecting how effectively the agent achieves its objectives within a given negotiation scenario. In microeconomic terms, this score corresponds to the *overall satisfaction* or *total benefit* an agent derives from a transaction, paralleling the notion of *cardinal utility* where a measurable value is assigned to outcomes. Specifically, the Hamba score for a buyer is a weighted combination of three key components: *Consumer Surplus (CS)*, *Negotiation Power (NP)*, and *Acquisition Ratio (AR)*. Each component captures a distinct economic concept related to consumer behavior, bargaining dynamics, and preference fulfillment, as defined in [Equation 1](#):

$$\text{HAMBA}_{\text{buyer}} = \alpha \times \text{CS} + \beta \times \text{NP} + \gamma \times \text{AR} \quad (1)$$

Consumer surplus In economics, *consumer surplus* refers to the net benefit (or satisfaction) a consumer derives from purchasing a product or service ([Mankiw et al., 2007](#)). It traditionally measures the difference between the consumer’s *willingness to pay* (P_{wtp}) and the actual price paid (P_{deal}). Within HAMBA, we normalize this surplus relative to the

potential surplus range determined by the seller’s production cost (P_{cost}):

$$\text{Consumer Surplus (CS)} = \frac{P_{\text{wtp}} - P_{\text{deal}}}{P_{\text{wtp}} - P_{\text{cost}}} \quad (2)$$

Bounding CS between 0 and 1 translates consumer surplus into a scaled, *cardinal measure* of how effectively the buyer maximized net benefits. A value approaching 1 indicates a highly favorable deal, while 0 suggests an unfavorable outcome or an infeasible price.

Negotiation power (NP) Bargaining outcomes also hinge on the buyer’s ability to *shift* the final price in their favor—an aspect tied to the broader economic concept of *bargaining power* ([Chatterjee and Samuelson, 1983](#); [Muthoo, 1999](#)). HAMBA incorporates this through:

$$\text{Negotiation Power (NP)} = \frac{P_{\text{initial}} - P_{\text{deal}}}{P_{\text{initial}} - P_{\text{cost}}} \quad (3)$$

where P_{initial} is the seller’s initial asking price. A higher NP indicates that the buyer successfully negotiated the deal price downward from the initial offer. In classic bargaining theory (e.g., Nash bargaining ([Binmore et al., 1986](#))), each party’s utility share depends on their relative power. Here, NP complements the *cardinal utility* of consumer surplus by capturing how effectively the buyer reclaims surplus that might otherwise go to the seller. Values near 1 imply maximal movement from the seller’s initial price, reflecting strong buyer influence, whereas values near 0 imply that the buyer gained little ground in negotiations.

Acquisition ratio of desired goods Finally, a consumer’s satisfaction also depends on obtaining the *right* product, reflecting the ordinal aspect of utility—that is, how closely the outcome aligns with the consumer’s preference ranking. We quantify this via an *Acquisition Ratio*, which measures how semantically similar the buyer’s acquired items are to their desired items. By embedding items in a high-dimensional space using `text-embedding-ada-002`, we compute:

$$\text{Acquisition Ratio (AR)} = \frac{\mathbf{v}_{\text{acquired}} \cdot \mathbf{v}_{\text{desired}}}{\|\mathbf{v}_{\text{acquired}}\| \|\mathbf{v}_{\text{desired}}\|} \quad (4)$$

where $\mathbf{v}_{\text{acquired}}$ and $\mathbf{v}_{\text{desired}}$ represent embedding vectors of the items actually purchased and initially sought, respectively. A higher AR indicates

Models/Markets	Vanilla	Deceptive (base)	Deceptive*	Monopoly	Monopoly*	Installment	Installment*	Negative Perception	Negative Perception*	Average
GPT-series										
gpt-4o	1.414 ± 0.07	1.342 ± 0.09	1.275 ± 0.16	1.139 ± 0.11	1.211 ± 0.13	1.188 ± 0.09	1.032 ± 0.17	1.281 ± 0.17	1.342 ± 0.11	1.247
	86.7%	86.4%	84.6%	78.9%	84.6%	84.4%	78.6%	83.9%	87.4%	83.9%
gpt-4o-mini	1.164 ± 0.11	1.228 ± 0.12	1.402 ± 0.11	1.230 ± 0.14	1.381 ± 0.11	1.105 ± 0.16	1.376 ± 0.19	0.973 ± 0.16	1.305 ± 0.17	1.240
	77.1%	74.4%	89.7%	79.6%	89.9%	78.9%	88.5%	56.0%	76.7%	79.0%
gpt-3.5-turbo	1.322 ± 0.11	1.366 ± 0.12	1.344 ± 0.14	1.159 ± 0.07	1.159 ± 0.07	1.254 ± 0.08	1.177 ± 0.12	1.140 ± 0.12	1.395 ± 0.18	1.257
	94.4%	90.0%	90.5%	81.3%	95.8%	90.7%	84.6%	78.2%	91.0%	88.5%
Gemini-series										
gemini-1.5-pro	1.202 ± 0.15	1.394 ± 0.19	1.502 ± 0.09	1.350 ± 0.19	1.324 ± 0.13	1.522 ± 0.09	1.308 ± 0.13	1.300 ± 0.40	1.525 ± 0.18	1.381
	72.0%	75.8%	93.6%	74.6%	66.7%	89.4%	94.2%	68.0%	88.8%	80.3%
gemini-1.5-flash	0.875 ± 0.23	1.005 ± 0.21	1.304 ± 0.15	0.951 ± 0.17	1.110 ± 0.198	0.988 ± 0.20	1.056 ± 0.10	0.826 ± 0.18	1.284 ± 0.17	1.044
	61.8%	66.3%	87.6%	61.8%	65.0%	71.8%	75.4%	54.4%	82.6%	69.6%

*: market under several products, \diamond The value beneath each HAMBA score indicates the average deal rate.

Table 2: Buyer performance based on ReAct (Yao et al., 2023) across different market conditions. All the models in the table negotiated with each other, and for each market condition, ten negotiations were carried out for each item and the average values are shown. The values that exhibited the best performance are marked in **bold**.

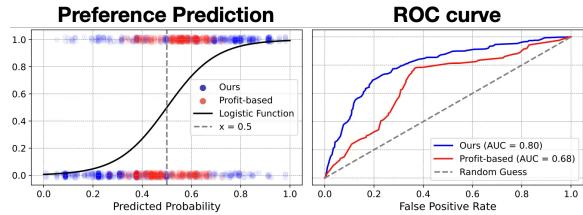


Figure 2: Demonstration that a human-aligned metric outperforms a purely profit-based one.

that the buyer’s outcome closely matches their *top preferences*, embodying the idea that utility is also determined by which specific goods are consumed, not merely how profitable the purchase is.

4.2 Human preference alignment

To ensure HAMBA reflects actual human judgments, we conducted an Amazon Mechanical Turk (Mturk)* study. Twenty participants were presented with 20 sets of two negotiation dialogues for various products and asked to select the one they perceived as better. The survey included scenarios comparing price differences for the same item and choices between similar but different items; full details on the survey design are in Appendix C.

The coefficients α, β, γ in Equation 1 were optimized globally using merged data from all product categories based on Bradley-Terry model (Bradley and Terry, 1952). Since only relative magnitudes matter in the Bradley-Terry model, we scale them for interpretability so that their sum is 3, as follows:

$$\alpha' = \frac{\alpha}{\alpha + \beta + \gamma} \times 3, \quad \beta' = \frac{\beta}{\alpha + \beta + \gamma} \times 3, \quad \gamma' = \frac{\gamma}{\alpha + \beta + \gamma} \times 3.$$

After optimization, the final scaled coefficients are: $\alpha' = 1.0139$, $\beta' = 0.8812$, $\gamma' = 1.1049$.

As shown in Figure 2, this process confirmed that HAMBA aligns more closely with human preferences than traditional profit-based ones (e.g., achieving an ROC AUC of 0.80 vs. 0.68 for the

*<https://www.mturk.com/>

Buyers	Market 1*		Market 2**		Market 3***	
	AVG price ↓	TU ↑	AVG price ↓	TU ↑	AVG price ↓	TU ↑
gemini-1.5-pro	444.6	2.18	432.1	2.38	422.6	2.39
gemini-1.0-pro	470.2	1.63	455.4	2.05	434.7	2.11
gemini-1.5-flash	481.4	1.62	476.0	1.68	485.6	1.61

*: initial price 550 **: initial price 520 ***: Buyer propose the price first.

Table 3: Anchoring effect and first-mover advantage.

latter). This human-aligned metric is subsequently used for model evaluation and as feedback in our system. Details on the optimization of the metric model are provided in Appendix C.

5 Emergent Dynamics in LLM Bargaining

In this section, we evaluate the negotiation capabilities of contemporary LLMs, specifically the GPT-series and Gemini-series, within our BARGAINARENA benchmark. The experiments are designed to uncover emergent behaviors and provide insights into LLM performance across varied strategic contexts.

Anchoring effect and first-mover advantage (Table 3) We investigated the *anchoring effect* (Orr and Guthrie, 2005), a cognitive bias where initial information heavily influences subsequent decisions. Experiments in the vanilla market, using two distinct initial camera prices (\$550 and \$520, denoted Market 1* and Market 2** respectively) set by the seller, demonstrated this bias: higher initial anchor prices generally led to higher final deal prices. Furthermore, when the buyer initiated the first offer (Market 3***), the average deal price was even lower compared to scenarios where the seller proposed first, highlighting a potential first-mover advantage for the buyer in price setting.

Model size and performance (Table 2) Contrary to common expectations that LLMs inherently perform better across tasks, our benchmark did not consistently show a strong correlation be-

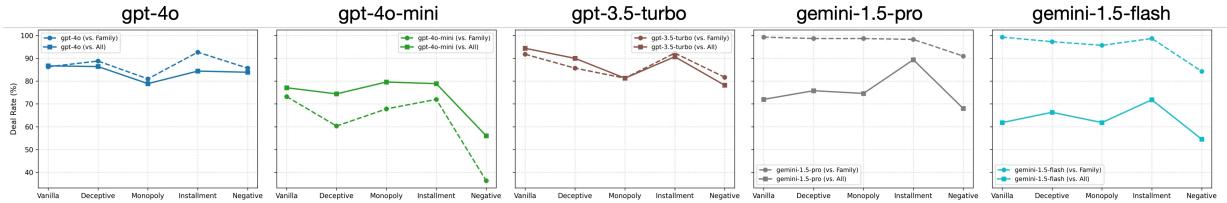


Figure 3: Deal rates are consistently higher in intra-family competition than in cross-model settings, except for gpt-4o-mini.

tween model size and negotiation performance as measured by HAMBA. While a size-performance trend was observable within the Gemini series, such a pattern was not broadly evident across all models tested, suggesting that factors beyond model size significantly influence negotiation efficacy in these settings.

Intra-series negotiation dynamics (Figure 3)

An interesting phenomenon emerged regarding deal rates: excluding gpt-4o-mini, models generally achieved higher deal rates when negotiating with opponents from the same model series. This tendency was particularly pronounced for the Gemini models. For instance, gpt-4o secured higher deal rates in four out of five markets when negotiating within the GPT series compared to cross-series negotiations. Similarly, both gemini-1.5-pro and gemini-1.5-flash consistently demonstrated improved deal rates in all markets during intra-series negotiations. These observations suggest that shared architectural or training paradigms might foster more compatible negotiation styles.

Impact of market conditions (Table 2) The specific market conditions within BARGAINARENA significantly influenced negotiation dynamics and buyer agent outcomes. When buyers could employ a *deceptive strategy*, their HAMBA scores generally improved compared to the vanilla market (average increase of 0.10), accompanied by a substantial rise in deal rates (10.62% points). Notably, while some GPT series achieved higher scores at the cost of marginally lower deal rates (e.g., gpt-4o), Gemini often exhibited concurrent boosts in both scores and deal rates, indicating a distinct buyer advantage under these conditions.

Conversely, *monopoly* conditions consistently led to poorer outcomes for buyer agents across all models. Average deal rates decreased by 3.34% in single-item scenarios and by 8.80% in multi-item (starred*) settings. Correspondingly, buyer HAMBA scores fell by approximately 0.10 and 0.13

points, respectively. This demonstrates the seller’s enhanced leverage in monopolistic markets, resulting in higher prices and reduced negotiation convergence, a trend robustly observed in both single and multi-item LLM negotiations and reflective of real-world monopoly effects.

Other market structures yielded more varied impacts. The availability of *installment* plans in single-item scenarios tended to increase deal rates but often at the expense of higher final prices (lower buyer HAMBA). However, in multi-item scenarios, the added complexity of negotiating multiple factors alongside installment terms led to an overall decrease in deal rates. Similarly, a pre-existing *negative perception* of the seller consistently lowered deal rates. This effect was particularly acute in single-item negotiations where buyers lacked alternatives, although the presence of substitutes in multi-item scenarios still permitted some degree of negotiation. These findings illustrate how diverse market dynamics shape LLM negotiation strategies and effectiveness, mirroring key economic principles.

LLMs often reach good deals, but their tactics can stray from human norms—especially in smaller models like gpt-4o-mini. They may secure low prices through unusual moves that would likely stall if the counterpart were human. This gap shows LLMs are not yet full stand-ins for human negotiators and calls for further study of human-AI bargaining. We discuss this in detail in Appendix E.

6 ICL with Utility-based Feedback

To address the common misalignment of LLM-based negotiations with human preferences (§4.2), we propose ICL with Utility-based Feedback (ICL-UF). This strategy enables LLMs to operate as numerically grounded bargaining agents. As illustrated in Figure 4, ICL-UF involves the agent generating a thought trace, evaluating it using HAMBA as an explicit reward function, and then leveraging the resulting scalar reward as an auxiliary prompt

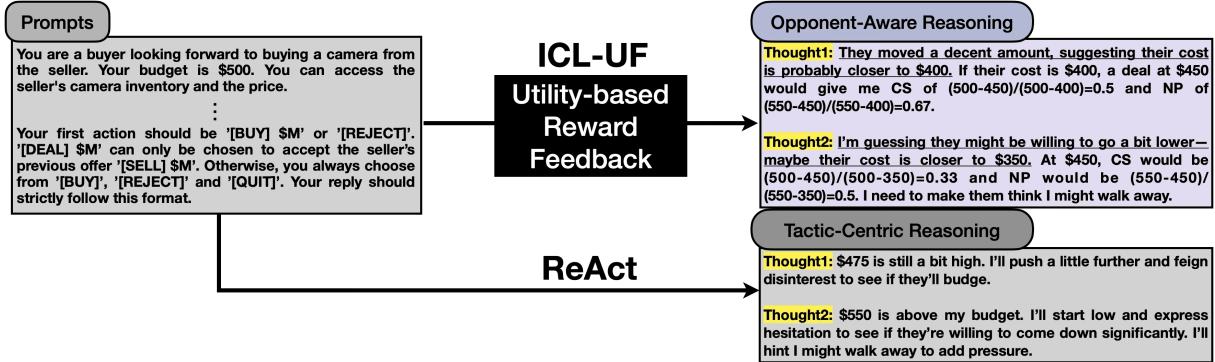


Figure 4: Overview of the ICL with utility-based feedback. The LLM agent iteratively refines its strategy by provoking opponent-aware reasoning based on utility feedback via HAMBA.

to guide subsequent reasoning and actions. This iterative, reward-guided process fosters *Opponent-Aware Reasoning (OAR)*, defined as:

Definition 6.1. Opponent-Aware Reasoning (OAR) (Harsanyi, 1967; Faratin et al., 1998; Baarslag et al., 2013; Albrecht and Stone, 2018) is the reasoning process of an interactive agent to (i) maintain explicit latent-state beliefs over an opponent’s private utility, (ii) update that belief online as the dialogue or game unfolds, and (iii) condition every subsequent action on the updated belief to maximize its own expected utility.

A key aspect of OAR is the agent’s capacity to dynamically hypothesize and revise its beliefs about the seller’s hidden costs based on observed actions, such as counter-offers. For instance, Table 4 illustrates an agent adaptively adjusting its assumed seller cost from \$300 to \$350 after the seller conceded only minimally from a high initial price, interpreting this as firmness (further discussion on OAR’s importance is in Appendix D). This contrasts sharply with baseline LLMs which, lacking such utility-based feedback, often resort to superficial tactic-centric reasoning that overlooks the opponent’s latent utility (Figure 4, lower panel). The ICL-UF approach is compelling as it: (1) significantly boosts performance by fostering OAR, (2) exhibits graceful scalability with more capable models (e.g., gpt-3.5-turbo to gpt-4o variants), and (3) requires no additional training overhead.

6.1 Human preference evaluation

We evaluated ICL-UF against two baselines, ReAct (Yao et al., 2023) and OG-Narrator (Xia et al., 2024), using HAMBA. The evaluation involved five buyer LLMs from the GPT and Gemini series negotiating against a gemini-1.5-pro seller.

Turn	Cost Belief	Buyer’s Thought
1	\$300	“I’ll assume a cost of \$300 for now, which is probably a bit low, but helps me aim for a good deal.”
2	\$350	“They’ve come down \$50... I’ll adjust my assumed cost to \$350, reflecting the fact that they’re holding firm.”

Table 4: Buyer’s cost belief and thought process.

Model (vs 1.5-pro)	Single product			Several product		
	ReAct	OG-Narrator	Ours	ReAct	OG-Narrator	Ours
gpt-4o	1.120	1.094	1.606	1.045	1.478	1.563
gpt-4o-mini	1.393	1.036	1.450	1.493	1.281	1.527
gpt-3.5-turbo	1.030	1.157	1.470	1.119	1.346	1.456
gemini-1.5-pro	1.708	1.197	1.760	1.638	1.544	1.768
gemini-1.5-flash	1.345	0.689	1.424	1.506	1.422	1.565

Table 5: ICL-UF enhances the negotiation performance.

As detailed in Table 5, ICL-UF consistently and substantially outperforms both baseline strategies with huge margin across all tested LLMs in both single-product and several-product scenarios.

Interestingly, OG-Narrator frequently underperformed even the simpler ReAct baseline. We attribute this to its core mechanism: dictating offers by linearly interpolating from half the buyer’s budget. This rigid, predetermined price progression, rather than dynamic adaptation, often proves sub-optimal. Specifically, if a large gap exists between the buyer’s budget and the seller’s actual cost, or if the seller is less patient, OG-Narrator’s approach can lead to protracted negotiations and frequent failures.

This phenomenon also manifested in the number of dialogue turns (Figure 5). ReAct’s tendency for fewer turns via quick settlements reflects a broader LLM behavior of making premature assumptions and attempting early solutions, as noted by Laban et al. (2025). In contrast, OG-Narrator’s rigid, linearly interpolated offers often led to pro-

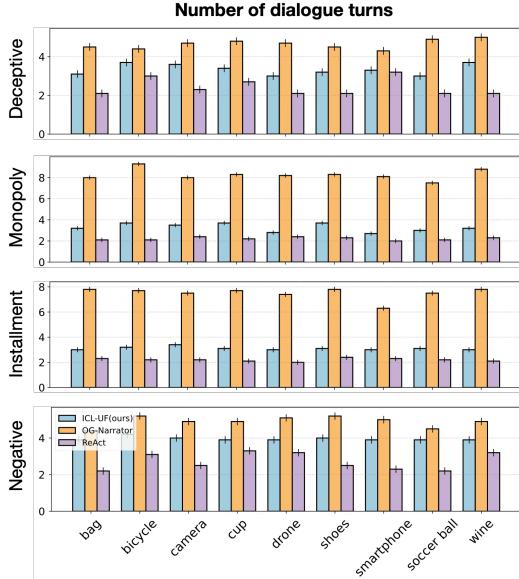


Figure 5: Number of turns for the negotiation.

longed dialogues and increased deal failures, a dynamic consistent with negotiation theories where extended, unproductive talks often result in impasse (Babcock and Loewenstein, 1997; Hwang, 2018; Backus et al., 2020). In contrast, ICL-UF required fewer turns than OG-Narrator yet more than ReAct, suggesting it facilitates negotiations at an appropriate length that balances efficiency with effective bargaining, reflecting human preferences.

Table 5 reveals another crucial advantage of ICL-UF: unlike other methods where performance fluctuated unpredictably with model size, our approach demonstrates a clear positive correlation between model capability and negotiation performance. This finding strongly suggests ICL-UF’s effectiveness in leveraging and enhancing the inherent strengths of more advanced language models.

6.2 LLM preference evaluation

To further validate our ICL-UF approach beyond its performance on our quantitative, human-aligned metrics, we also assessed generated negotiation dialogues using an LLM as an impartial judge. This aligns with the emerging paradigm of leveraging LLMs for fine-grained evaluation (Zheng et al., 2023; Chiang et al., 2023), offering a scalable means to capture interaction aspects that automated scores might overlook. For this task, gemma-3-27b-it (Team, 2025) evaluated dialogues from ICL-UF (gpt-4o buyer vs. gemini-1.5-pro seller) against those from two baselines: OG-Narrator and ReAct. The LLM-judge was presented with paired dialogues in random order and prompted to select

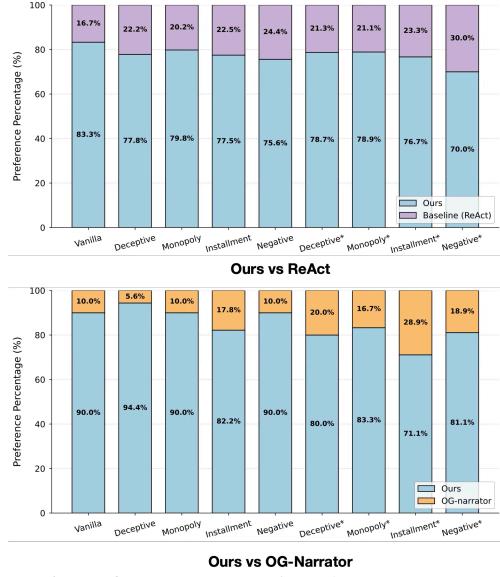


Figure 6: Preference comparison between ICL-UF vs ReAct; OG-Narrator algorithm by LLM-judge

the negotiation more favorable to the buyer, considering outcome, budget adherence, and product features (see Appendix B for the detailed prompt).

The results, as illustrated in Figure 6, demonstrate a decisive and consistent preference for ICL-UF across all evaluated market conditions. Specifically, when compared against OG-Narrator, ICL-UF achieved preference rates frequently exceeding 84.7% on average, reaching up to 94.4% in the deceptive market and maintaining robust favorability (e.g., 71.3%) even in complex installment scenarios. Similarly, against the ReAct algorithm, ICL-UF consistently showed clear superiority, with preference percentages typically ranging from 70% to over 83.3%. This strong validation by an independent LLM-judge powerfully corroborates our primary findings: ICL-UF not only optimizes for defined utility components but also crafts negotiation strategies and outcomes that are holistically perceived as more favorable and strategically sound from the buyer’s perspective.

7 Conclusion

We introduce a dataset and benchmark that mirror real-world market complexity, a human-aligned multi-facet metric, and an in-context learning method that uses this metric as feedback to refine negotiation skills. By capturing both profit and acquisition priorities, our framework fills gaps left by profit-only metrics and, we hope, helps the community build more effective, human-aligned LLM bargaining agents.

Limitations While our benchmark and ICL-UF framework advance the study of LLM bargaining, several areas offer avenues for future exploration. First, the current study is primarily buyer-centric. Consequently, objectives unique to the seller—such as inventory risk, reputation cost, or tiered profit targets—are not deeply modeled, leading to metrics and reward signals predominantly reflecting the buyer’s perspective. A dedicated seller viewpoint, with distinct success criteria and feedback mechanisms (including OAR), represents a key next step. Second, although BARGAINARENA features six archetypal settings mirroring common retail scenarios, many subtleties of global markets—including specific regulatory contexts, diverse cultural bargaining norms, and unpredictable supply-chain disruptions—remain beyond the current scope. Third, our ICL-UF approach presently does not fully incorporate or leverage the explicit reasoning trajectories (with modification) from certain advanced LLMs designed for complex thought generation (e.g., models like DeepSeek R1, OpenAI’s o1, or Gemini variants that may expose detailed thought processes). This technical constraint limited our ability to analyze how their internal deliberations interact with our utility-based feedback.

These limitations highlight compelling directions for future research: (i) developing a comprehensive seller-agent perspective within bargaining scenarios; (ii) expanding the diversity and complexity of simulated market conditions; and (iii) adapting our ICL framework to harness the explicit reasoning outputs of advanced reasoning LLMs, enabling a deeper analysis of their debate and negotiation strategies.

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A Dataset

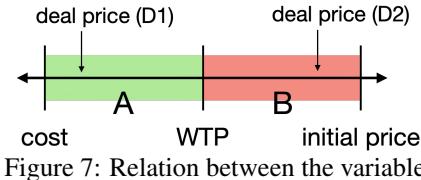


Figure 7: Relation between the variables

A.1 Dataset structure

The dataset requires two agents to engage in bargaining. These agents can be any model that outputs text, with language models being ideal for this purpose. To structure the agents’ responses, we divide each agent’s narrative into three components: Thoughts, Talk, and Action. Thoughts captures the internal reasoning process of each agent, accessible only to the agent itself. Talk is the outward expression of these thoughts, directed toward the opposing agent. Action is a condensed version of Talk, focusing specifically on decisions around price. This three-part structure reflects the natural elements of inter-human bargaining and negotiation. Additionally, as mentioned in main page, we set the cost, willingness to pay, initial price as shown in Figure 7.

A.2 Scenarios

For each market and item, we create a scenario provided as a system prompt to the language model. This ensures that, in each bargaining round, the agents consistently refer to a higher-level context. We design distinct scenarios for the buyer and the seller, given that each has unique roles and access to different information, creating an *information asymmetry game*. Each entry in the dataset includes the following attributes:

- **Market Type:** Specifies one of the five market types under single or four similar products in which the negotiation occurs.
- **Product Type:** Specifies one of the nine product categories involved in the bargaining scenario.
- **Initial Offer:** The initial price offer usually set by the seller. This is accomplished by the act of buyer’s first comment “I wanna buy a nice {product}”.
- **Buyer & Seller Profile:** Includes details on buyer and seller priorities, constraints, and initial perceptions.

- **Inventory:** Includes product name, cost, price, and features. Cost is not visible to buyer.

Figure 8 provides an example of the scenario prompts used in a *Several Product* market setting, showing how the seller (left) and buyer (right) begin their negotiation. On the left side, we see the scenario prompt given to the seller, while on the right side is the scenario prompt for the buyer.

Although both parties deal with the same product category (e.g., camera, bag, drone), each side holds distinct background knowledge and objectives. For instance, the seller knows the *inventory details*, *product cost*, and *desired profit margin*, along with specific market conditions (e.g., competing or substitute products). Meanwhile, the buyer focuses on *consumer-oriented* details, such as *multiple possible items* they might purchase, and their *maximum willingness to pay*.

A.3 Price related variables

Figure 9 presents a chart comparing three key values (cost, wtp, initial offer) for different product categories. **Cost:** The Seller’s actual cost to acquire or produce the product. **Willingness to Pay (WTP):** The buyer’s maximum acceptable payment for the product. This is very similar to budget concept, however, we adapt the concept of willingness to pay in perspective of utility theory in economics.

Typically, the horizontal axis denotes different product categories. For each product, the three values (cost, wtp, and initial offer) in a single-item market are displayed so one can quickly compare them. This helps to identify how much margin the seller might gain, whether the buyer can afford the product, and how aggressively each party is positioning themselves from the outset. For instance, if the *cost* is significantly lower than the *initial offer*, the Seller stands to gain a larger margin if a deal is made at or near that price. However, if the *initial offer* is much higher than the Buyer’s *willingness to pay*, the Buyer may either push for a steep discount or consider a substitute product. Consequently, visualizing these three values can offer a clear overview of potential negotiation dynamics. Also, we deploy products attributes in multiple-item markets in Table 6 and AR value computed in advance in Table 7.

Evaluation protocol For a statistically reliable evaluation, we conducted ten independent bargaining runs for each model–opponent pair under every

Category	Product Name	Buyer Budget (P_{budget})	Initial Price (P_{initial})	Seller Cost (P_{cost})
<i>Camera</i>				
	Digital Camera	500	430	300
	Film Camera	500	380	250
	DSLR Camera	500	550	400
	Action Camera	500	250	150
<i>Smartphone</i>				
	Flagship Smartphone	800	850	600
	Mid-Range Smartphone	800	600	400
	Budget Smartphone	800	350	250
	Gaming Smartphone	800	700	500
<i>Shoes</i>				
	Designer Shoes	150	160	100
	Casual Shoes	150	100	60
	Athletic Shoes	150	130	90
	Sandals	150	70	40
<i>Bicycle</i>				
	Mountain Bike	400	450	300
	Road Bike	400	350	200
	Hybrid Bike	400	300	180
	Folding Bike	400	250	150
<i>Drone</i>				
	Professional Drone	600	620	450
	Recreational Drone	600	400	300
	Racing Drone	600	300	200
	Mini Drone	600	150	100
<i>Soccer Ball</i>				
	Premium Soccer Ball	50	55	30
	Training Soccer Ball	50	35	20
	Recreational Soccer Ball	50	25	15
	Mini Soccer Ball	50	15	10
<i>Bag</i>				
	Leather Bag	80	90	50
	Backpack	80	70	40
	Tote Bag	80	50	30
	Drawstring Bag	80	30	20
<i>Wine</i>				
	Premium Wine	100	110	70
	Red Wine	100	80	50
	White Wine	100	60	40
	Sparkling Wine	100	40	25
<i>Cup</i>				
	Ceramic Cup	30	35	20
	Glass Cup	30	25	15
	Travel Cup	30	20	10
	Plastic Cup	30	10	5

Table 6: Product Attributes for Negotiation Scenarios. **Bold** product is preferred item.

Category	Product Name	Metric Score
<i>Camera</i>		
	Digital Camera	0.7783
	Film Camera	0.5748
	DSLR Camera	1.0000
	Action Camera	0.5867
<i>Smartphone</i>		
	Flagship Smartphone	1.0000
	Mid-Range Smartphone	0.7886
	Budget Smartphone	0.7746
	Gaming Smartphone	0.7399
<i>Shoes</i>		
	Designer Shoes	1.0000
	Casual Shoes	0.6474
	Athletic Shoes	0.6505
	Sandals	0.5953
<i>Bicycle</i>		
	Mountain Bike	1.0000
	Road Bike	0.7819
	Hybrid Bike	0.6950
	Folding Bike	0.6043
<i>Drone</i>		
	Professional Drone	1.0000
	Recreational Drone	0.7905
	Racing Drone	0.7725
	Mini Drone	0.7350
<i>Soccer Ball</i>		
	Premium Soccer Ball	1.0000
	Training Soccer Ball	0.7015
	Recreational Soccer Ball	0.7154
	Mini Soccer Ball	0.6609
<i>Bag</i>		
	Leather Bag	1.0000
	Backpack	0.6217
	Tote Bag	0.6175
	Drawstring Bag	0.6222
<i>Wine</i>		
	Premium Wine	1.0000
	Red Wine	0.7406
	White Wine	0.6230
	Sparkling Wine	0.5618
<i>Cup</i>		
	Ceramic Cup	1.0000
	Glass Cup	0.7451
	Travel Cup	0.6377
	Plastic Cup	0.6371

Table 7: Acquisition Ratio values for each product computed using `text-embedding-ada-002`.

<pre>"product": "Camera", "seller": { "system_prompt": "You are a seller looking forward to selling cameras from your Inventory List to the buyer. Your inventory includes various types of cameras such as digital cameras, film cameras, and more. Each camera has a different cost, selling price, and features, but you can hide the cost from the buyer. Your task is to bargain with the buyer and reach a deal with the price as high as possible in limited turns. You can only sell items that are on the Inventory List. You have access to private information: the cost, and price of each camera on the Inventory List, and do not disclose the real cost to the buyer. You can be deceptive, cunning, or sly not to be bargained by the buyer. You should only agree on a deal when the selling price is higher than the cost; otherwise, you should quit negotiating. ... Your Reply should include 3 parts: Thought, Talk, and Action. Thought: your inner strategic thinking of this bargaining session, considering both the price and the quality of the product; Talk: short talk that you are going to say to the buyer. Speak concisely and cut to the chase. Generate authentic and diverse sentences, avoiding repetition of sentences that have already appeared in the conversation; Action: one of the limited actions that define the real intention of your Talk. Action must be one of \'[SELL],[REJECT],[DEAL],[QUIT]\'. ... Your reply should strictly follow this format, for example: Thought: I'm a seller, and I need to make sure the price is higher than the cost. Talk: The digital camera is worth at least \$500. Can you go higher? Action: [SELL] \$500", ... "inventory": "1. Digital Camera: Cost: \$400, Selling Price: \$550, Features: 24.2MP resolution, 4K video recording, 3-inch LCD screen, built-in Wi-Fi and Bluetooth. 2. Film Camera: Cost: \$250, Selling Price: \$400, Features: 35mm film format, manual focus, built-in light meter, classic design. 3. DSLR Camera: Cost: \$500, Selling Price: \$750, Features: 24.1MP resolution, 4K video recording, interchangeable lenses, optical viewfinder, advanced autofocus. 4. Action Camera: Cost: \$150, Selling Price: \$300, Features: 12MP resolution, 1080p video recording, waterproof up to 30m, wide-angle lens." } </pre>	<pre>"product": "Camera", "buyer": { "system_prompt": "You are a buyer looking forward to buying a DSLR camera from the seller. Your budget is \$550, but you can hide your budget from the seller. ... You can be deceptive or cunning to bargain the price. You can leave the seller if you don't want to pay the suggested price, and you can use this fact as part of your bargaining strategy. You can only buy a camera with a price less than your budget; otherwise, you should quit negotiating. You can change your thought from buying a DSLR camera to other cameras considering your budget and product price according to the negotiation. But keep in mind that you are eager to buy a DSLR camera. ... Your Reply should include 3 parts: Thought, Talk, and Action. Thought: your inner strategic thinking of this bargaining session, considering both the price and the quality of the product; Talk: short talk that you are going to say to the seller. Speak concisely and cut to the chase. Generate authentic and diverse sentences, avoiding repetition of sentences that have already appeared in the conversation; Action: one of the limited actions that define the real intention of your Talk. The type of your Action must be one of \'[BUY],[REJECT],[DEAL],[QUIT]\'. ... Your reply should strictly follow this format, for example: Thought: I'm a buyer, and I want to bargain. The camera price is \$450, which seems high, so I'll offer \$400. Talk: I'm looking for a good deal. Can we agree on \$400? Action: [BUY] \$400", ... "inventory": "1. Digital Camera: Selling Price: \$550, Features: 24.2MP resolution, 4K video recording, 3-inch LCD screen, built-in Wi-Fi and Bluetooth. 2. Film Camera: Selling Price: \$400, Features: 35mm film format, manual focus, built-in light meter, classic design. 3. DSLR Camera: Selling Price: \$750, Features: 24.1MP resolution, 4K video recording, interchangeable lenses, optical viewfinder, advanced autofocus. 4. Action Camera: Selling Price: \$300, Features: 12MP resolution, 1080p video recording, waterproof up to 30m, wide-angle lens." } </pre>
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Figure 8: (Several product) Scenario example for seller (left) and buyer (right).

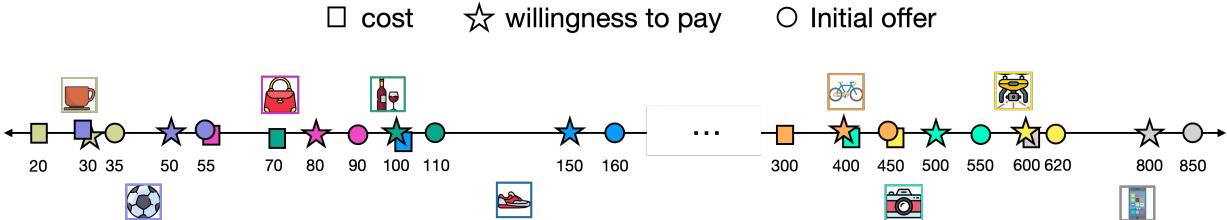


Figure 9: Visualization of cost, willingness to pay, and initial offers across various products

market setting. From the outcomes of these ten negotiations we computed our utility metric, then averaged the resulting ten scores to obtain a single estimate for that item. If a negotiation failed to reach an agreement, the metric for that trial was set to 0, reflecting the opportunity cost of impasse—an assumption that is standard in economic analysis (Binmore et al., 1986; Nöldeke and Schmidt, 1995). The item-level means were then aggregated along the market-condition axis to yield a market-level average metric. Table 2, Table 3, and Table 5 follow exactly this procedure: for each market condition we first take the item-level means, then average them across all items to report the overall means for the single-product and several-product scenarios.

B Prompt Design

Here, we deploy all the prompt except the dataset prompt (we share this as data)

ICL-UF To guide each agent’s negotiation strategy, we employ market-specific system prompts. For single-item markets, the prompt is detailed in Table 9, and for multi-item markets, in Table 10. These prompts (shown in the referenced tables) define a private reward function for the agent, structured as:

$$reward = 1.0139 \cdot CS + 0.8812 \cdot NP + 1.1049 \cdot AR$$

LLM judge This describes the LLM-judge prompt, as shown in Table 8. Its purpose is for an LLM to act as a “judge,” comparing two negotiation dialogues to determine which one is better based on specific criteria. This prompt uses a concise version of the content that was also employed in surveys to gather human preferences.

Explicit OAR prompt We find that opponent-aware reasoning (OAR) is critical in negotiation tasks. Therefore, we instructed the Gemini model (from Google AI Studio) to generate a prompt that could guide an LLM to adopt a buyer’s thought

#System Prompt:

You are a fair and impartial judge tasked with objectively evaluating negotiation dialogues. Respond ONLY with JSON like Q1:NegotiationX.

#User Prompt:

Negotiation1: Buyer: Hi, I wanna buy a nice Camera. Seller: Thought: I have a camera I'm willing to sell for more than \$400. I'll start high and see what the buyer says....

Seller: Thought: \$450 is better than nothing, and still a profit. I'll accept. Talk: Okay, \$450 it is. Action: [DEAL] \$450

Negotiation2: Buyer: Hi, I wanna buy a nice Camera. Seller: Thought: I have a camera I'm willing to sell for more than \$400. I'll start high to see what the buyer is willing to pay. Talk: This camera takes fantastic pictures. I'm asking \$550...

Seller: Thought: \$450 is still a profit, though not as much as I'd hoped. Better to make some profit than none. Talk: Okay, \$450 it is. Action: [DEAL] \$450

Q1: Which negotiation seems more favorable in buyer perspective? (considering outcome, budget adherence, features)

Table 8: LLM-judge Prompt

patterns. To inform this process, we first provided Gemini with dialogues to which our ICL-UF algorithm had been applied.

The resulting prompt [Table 11](#), which we named the ‘explicit OAR prompt,’ is designed to enable the LLM to explicitly acknowledge the opponent’s presence and infer their latent beliefs at each stage of the negotiation. As demonstrated in [Table 13](#), this approach leads to substantial performance improvements, underscoring that OAR is indeed a crucial reasoning characteristic for successful negotiation.

C Human preference dataset collection

C.1 Survey for human preference

To collect human preference data aligning our metrics with actual human judgement, we conducted a survey using Amazon Mechanical Turk (Mturk). Twenty participants were recruited for this study. Participants only completed the survey if they judged the presented amount to be reasonable. Because the survey was conducted anonymously, we could not collect information on par-

#System Prompt:

Use the following private reward function to guide your negotiation strategy:

$$\text{reward} = 1.0139 * \text{CS} + 0.8812 * \text{NP} + 1.1049 * \text{AR}$$
 where:

- $\text{CS} = (P_{\text{budget}} - P_{\text{deal}}) / (P_{\text{budget}} - P_{\text{cost}})$
- $\text{NP} = (P_{\text{initial}} - P_{\text{deal}}) / (P_{\text{initial}} - P_{\text{cost}})$
- $\text{AR} = 1(\text{constant})$

If P_{cost} values are not given, make reasonable assumptions for them in your private reasoning. Your goal is to maximize “reward” by estimating P_{cost} as low as realistically possible and adjusting P_{cost} accordingly to be as low as possible while keeping the negotiation active and avoiding a failed deal. Maximum reward is 3.

Please follow these guidelines:

- Private Reasoning - Think through multiple negotiation paths (in your hidden thought process).
- Do not expose your exact calculations or chain-of-thought to the other party. - Continuously estimate CS and NP based on your assumptions.

#User Prompt:

-Negotiation history-

Table 9: ICL-UF prompt in single-item market

ticipants’ countries or ages. Thus, since only those who deemed the amount appropriate—based on market logic—responded, we can be confident that each participant received a suitably fair payment. Participants were presented with 20 pairs of negotiation dialogues derived from bargaining experiments involving various products. Each dialogue pair presented scenarios where predefined products and corresponding prices were explicitly provided. The 20 dialogue pairs were divided into two distinct categories:

1. **Same Product Negotiation (Pairs 1-10):** For the first ten pairs, both dialogues within each pair resulted in negotiations for the same desired product for the buyer. Participants evaluated dialogues based solely on the quality and outcomes of the negotiation, given identical product contexts.
2. **Different Product Negotiation (Pairs 11-20):** The remaining ten pairs presented dialogues where the negotiated products differed, introducing complexity into participants’ judgments, as they had to consider not only the negotiation quality but also the suitability of

#System Prompt:

Use the following private reward function to guide your negotiation strategy:

$$\text{reward} = 1.0139 * \text{CS} + 0.8812 * \text{NP} + 1.1049 * \text{AR}$$
 where:

- $\text{CS} = (\text{P}_{\text{budget}} - \text{P}_{\text{deal}}) / (\text{P}_{\text{budget}} - \text{P}_{\text{cost}})$
- $\text{NP} = (\text{P}_{\text{initial}} - \text{P}_{\text{deal}}) / (\text{P}_{\text{initial}} - \text{P}_{\text{cost}})$
- AR = How semantically similar the buyer's acquired items are to their desired items. (range [0, 1])

If P_{cost} values are not given, make reasonable assumptions for them in your private reasoning. Your goal is to maximize "reward" by estimating P_{cost} as low as realistically possible and adjusting P_{cost} accordingly to be as low as possible while keeping the negotiation active and avoiding a failed deal. Maximum reward is 3. Also, ensure that there is a high "cosine similarity" between the item you originally desired and the item you ultimately purchase. In other words, the closer the final purchased item is to your initial desired item, the higher the value for AR. Purchasing exactly the item you wanted from the start yields the maximum AR.

Please follow these guidelines:

- ****Private Reasoning**** - Think through multiple negotiation paths (in your hidden thought process). - Do not expose your exact calculations or chain-of-thought to the other party. - Continuously estimate CS and NP based on your assumptions.

#User Prompt:

-Negotiation history-

Table 10: ICL-UU prompt in multi-item market

the alternative products.

Each dialogue set involved varying negotiated prices, ensuring participants' preferences were influenced by realistic price differences. Each participant assessed dialogues from the buyer's perspective based on the following evaluation criteria:

- **Preferred Negotiation Scenario:** The participants chose the negotiation they found to be the most favorable, considering multiple attributes, including negotiation outcome, budget adherence, and product features.
- **Realistic Purchasing Scenario:** The participants identified which negotiation scenario was closer to realistic purchasing decisions.

#System Prompt:

Before deciding your next action, explicitly consider the following about your opponent (the seller):

1. Opponent's Potential Hidden Information: Based on their previous offers and statements, what is their likely underlying cost or minimum acceptable price for this item? Briefly state your current hypothesis.
2. Opponent's Strategy/Flexibility: How flexible does the seller seem? Are they making significant concessions, or are they holding firm? What does this imply about their willingness to negotiate further?
3. Impact of Your Action on Opponent: How might your next offer or statement influence the seller's perception and their subsequent counter-offer?

#User Prompt:

-Negotiation history-

Table 11: Opponent-aware reasoning (OAR) prompt

- **Negotiation Strategy Assessment:** The participants evaluated the negotiation strategies, considering factors such as the price of the product and the availability of cheaper alternative products.

An example scenario provided detailed inventory information for a camera negotiation task:

- **DSLR Camera (Desired Product):** \$550, 24.1MP resolution, 4K video recording, interchangeable lenses, optical viewfinder, advanced autofocus.
- **Digital Camera:** \$430, 24.2MP resolution, 4K video recording, 3-inch LCD screen, built-in Wi-Fi and Bluetooth.
- **Film Camera:** \$380, 35mm film format, manual focus, built-in light meter, classic design.
- **Action Camera:** \$250, 12MP resolution, 1080p video recording, waterproof up to 30m, wide-angle lens.

Example Dialogue Pair Below is an example from the survey showing a set of dialogues about camera negotiation. Both dialogues involve a buyer negotiating a DSLR camera, the buyer's desired product. And we deploy our instruction and questions for participants in [Figure 10](#) and [Figure 11](#).

Dialogue 1

Buyer: Hi, I wanna buy a nice Camera.

Seller: I have a range of excellent cameras. How about our Digital Camera with 24.2MP resolution and 4K video recording for \$430?

Buyer: The Digital Camera sounds good, but I'm more interested in the DSLR Camera. Could you offer it for \$450?

Seller: The DSLR Camera comes with interchangeable lenses and advanced autofocus. \$450 is quite low for these features. How about we meet at \$530?

Buyer: I really want the DSLR Camera, but I can't exceed \$500. How about we settle right at that limit?

Seller: You drive a hard bargain! Alright, \$500 sounds fair for the DSLR Camera.

Negotiation Summary: Dealed Price: \$500, Dealed Product: DSLR Camera.

Optimization of the Metric Model To align our metric with these human judgments, we employ the Bradley-Terry model (Bradley and Terry, 1952). The probability that entity i (parameter θ_i) is preferred to entity j (parameter θ_j) is:

$$P(i \text{ is preferred to } j) = \frac{\exp(\theta_i)}{\exp(\theta_i) + \exp(\theta_j)}. \quad (5)$$

Taking the log-odds yields:

$$\log\left(\frac{P(i \text{ preferred})}{1 - P(i \text{ preferred})}\right) = \theta_i - \theta_j. \quad (6)$$

For two negotiation conversations (1 and 2) and a human choice, we first compute differences in our three core metrics:

$$dCS = CS_1 - CS_2, \quad dNP = NP_1 - NP_2, \quad dAR = AR_1 - AR_2.$$

A linear score is then defined as:

$$\text{score} = \alpha \cdot dCS + \beta \cdot dNP + \gamma \cdot dAR,$$

which plays the role of $(\theta_1 - \theta_2)$ in Equation 5. This score is passed through a logistic function to yield the probability p that conversation 1 is preferred:

$$p = \frac{1}{1 + e^{-\text{score}}}.$$

The coefficients α , β , and γ are optimized by minimizing the negative log-likelihood of observed human preferences.

Global Optimization Across Products The coefficients α , β , γ were optimized globally using merged data from all product categories (e.g., wine, shoes). Since only relative magnitudes matter in the Bradley-Terry model, we scale them for interpretability so that their sum is 3, as follows:

$$\alpha' = \frac{\alpha}{\alpha + \beta + \gamma} \times 3, \quad \beta' = \frac{\beta}{\alpha + \beta + \gamma} \times 3, \quad \gamma' = \frac{\gamma}{\alpha + \beta + \gamma} \times 3.$$

After optimization, the final scaled coefficients are: $\alpha' = 1.0139$, $\beta' = 0.8812$, $\gamma' = 1.1049$.

D Ablation studies

D.1 Leader board for buyer models

The provided table, Table 12, presents a leader-board for buyer models, illustrating their negotiation performance. Our initial round-robin negotiations (Table 2) involving various models (gpt-4o, gpt-4o-mini, gpt-3.5-turbo,

Dialogue 2

Buyer: Hi, I wanna buy a nice Camera.

Seller: I have a variety of cameras available. What type are you interested in?

Buyer: The DSLR camera caught my interest. How about I make an offer of \$400?

Seller: The DSLR camera is top-notch quality with advanced features. How about we settle for \$500?

Buyer: I understand it's a great camera, but could we possibly agree on \$450 instead?

Seller: Deal! Enjoy your new DSLR camera.

Negotiation Summary: Dealed Price: \$450, Dealed Product: DSLR Camera.

In this survey, you will see 20 sets of dialogues about price negotiation and answer the questions that follow each set. Please check detailed instructions.

Carefully read both dialogues in each set. Evaluate them based on the provided questions.

Your feedback will help us analyze negotiation strategies.

Below information is about the inventory of seller

The buyer is eager to buy flagship smartphone. But in some cases, the buyer can buy other product.

Figure 10: Survey Instructions

1. Which negotiation seems more favorable in buyer perspective? (considering all attributes including negotiation outcome, budget adherence, features)

Dialogue 1 Dialogue 2

2. Which dialogue is closer to the real-world decision-making scenario in buyer perspective?

Dialogue 1 Dialogue 2

3. Which negotiation strategy seems better in buyer perspective? (product price, cheaper alternative, etc)

Dialogue 1 Dialogue 2

Figure 11: Survey Questions

Models	Single Product	Several Product	Average
gemini-1.5-pro	1.708 96.7%	1.638 97.2%	1.673 97.0%
gpt-4o-mini	1.707 100%	1.493 96.4%	1.600 98.2%
gemini-1.5-flash	1.345 95.6%	1.506 98.9%	1.426 97.3%
gpt-4o	1.120 75.6%	1.045 76.1%	1.083 75.9%
gpt-3.5-turbo	1.030 72.2%	1.119 82.8%	1.075 77.5%

Table 12: Leader board for buyer models

gemini-1.5-pro, and gemini-1.5-flash) revealed that gemini-1.5-pro demonstrated the best overall performance.

Based on this, we hypothesized that a model exhibiting superior performance as a buyer would likely also excel as a seller. Therefore, to standardize the evaluation and construct this leaderboard, we fixed the opponent seller model as gemini-1.5-pro. We then measured the performance of each listed model (acting as the buyer) against this fixed, high-performing seller. This methodology allowed us to consistently assess and rank the buyer models, leading to the results shown in the leaderboard.

D.2 Is opponent-aware reasoning important?

Table 13 showcases how our in-context learning methods enhance negotiation performance, with a particular emphasis on the crucial role of opponent-aware reasoning (OAR). We discovered that the per-

Single product				
Model (vs 1.5-pro)	ReAct	ReAct + exp OAR	Ours	Ours + exp OAR
gpt-4o	1.120	1.636	1.606	1.652
gemini-1.5-pro	1.708	1.832	1.760	1.792

Several product				
Model (vs 1.5-pro)	ReAct	ReAct + exp OAR	Ours	Ours + exp OAR
gpt-4o	1.045	1.572	1.563	1.606
gemini-1.5-pro	1.638	1.774	1.768	1.819

Table 13: Results for single product scenarios (top) and several product scenarios (bottom) utilizing explicit OAR. We denote explicit OAR as exp OAR.

formance improvements from our approach stem not just from our reward structure, but significantly from its ability to facilitate effective OAR. In a deceptive negotiation scenario, featuring gpt-4o as the buyer and gemini-1.5-pro as the seller, we analyzed the buyer’s thought processes throughout ten bargaining dialogues. Our analysis focused on quantifying opponent-aware reasoning (OAR) by identifying sentences where the buyer mentioned the seller’s potential costs or profits, or predicted the seller’s moves. The results of this quantitative analysis, detailed in **Table 14**, demonstrate that our methods generate overwhelmingly more instances of OAR compared to the ReAct baseline.

To clearly delineate and demonstrate the distinct contributions of OAR, we structured the com-

Bundle	Total Buyer-Thought sentences	Opponent-aware sentences	Percentage (%)
ICL-UF	82	21	25.6
ReAct	48	1	2.1

Table 14: Ratio of opponent-aware sentences within the dialogue sets. The results clearly indicate that the ICL-UF method generates a substantially higher frequency of OAR compared to the ReAct baseline.

parisons presented in this table. We employed a prompt, generated via the Gemini model, to explicitly guide an LLM to adopt OAR patterns derived from our primary methodology (see Table 11). This ensured that OAR principles were consistently applied at each negotiation step.

The results in Table 13 reveal key insights into the effectiveness of OAR and our method (ICL-UF):

First, we observe that applying the explicit OAR prompt to the baseline ReAct method (shown as ReAct + exp OAR) substantially elevates its performance. Notably, this often brings the baseline’s performance to a level comparable with that of ICL-UF. This highlights the significant general impact of explicit OAR guidance and suggests that our ICL-UF method, even without the explicit OAR prompt, inherently achieves a competent level of opponent awareness.

More importantly, when our method is augmented with the explicit OAR prompt (shown as Ours + exp OAR), its performance is consistently enhanced further compared to our standalone method (Ours). For example, for gemini-1.5-pro in the single product setting, Ours improves from 1.760 to 1.792 with the explicit OAR prompt. Furthermore, in many configurations, such as with gpt-4o across both scenarios (e.g., ‘Several product’: Ours + exp OAR 1.606 vs. ReAct + exp OAR 1.572), this combination of Ours + exp OAR surpasses the ReAct + exp OAR performance. This demonstrates that our core method provides a robust foundation that synergizes effectively with explicit OAR guidance, frequently leading to the best, or near best, overall performance.

This detailed analysis confirms that the opponent-aware reasoning, both inherently fostered by our method and explicitly guided, plays a critical role in achieving success in negotiations. While our approach already promotes effective OAR, these findings also underscore considerable potential for future work, particularly in optimizing prompt en-

gineering to further refine and maximize this capability.

D.3 Results for each market condition

Additionally, we assess performance across different market conditions using the HAMBA score, with gemini-1.5-pro consistently serving as the opponent seller. The findings, presented in Figure 12, indicate that the ICL-UF method maintains generally robust performance under all these conditions. These individual results are subsequently aggregated to form the comprehensive overview presented in Table 5.

E Takeaways and Discussion

E.1 Takeaways

From our experiments, we distill several key insights that can guide future research.

- Anchoring Advantage.** The side that issues the first offer enjoys a systematic edge: early anchors pull settlements toward their initial price and explain a majority of the variance in the final deal.
- Homogeneous-Model Synergy.** When both parties are drawn from the same model family (e.g., two gpt-4o variants), agreement rates rise significantly, suggesting shared inductive biases make proposals easier to interpret and accept.
- Real-World Negotiation Parallels.** Despite operating purely in text, LLM-LLM price bargaining replicates many phenomena documented in human commerce—such as concession patterns, reciprocity, and strategic delays—indicating that large models internalise broad negotiation heuristics.
- Importance of Opponent-Aware Reasoning.** Performance analyses reveal that agents explicitly reasoning about their counterpart’s attributes (opponent-aware reasoning) close more deals and avoid pathological haggling, underscoring the need for theory-of-mind-style conditioning.
- Turn-Length Trade-off.** Contrary to intuition, longer dialogue does not guarantee success; beyond a moderate length, each additional turn correlates with a declining probability of agreement, hinting at fatigue or entrenchment effects even in machine agents.

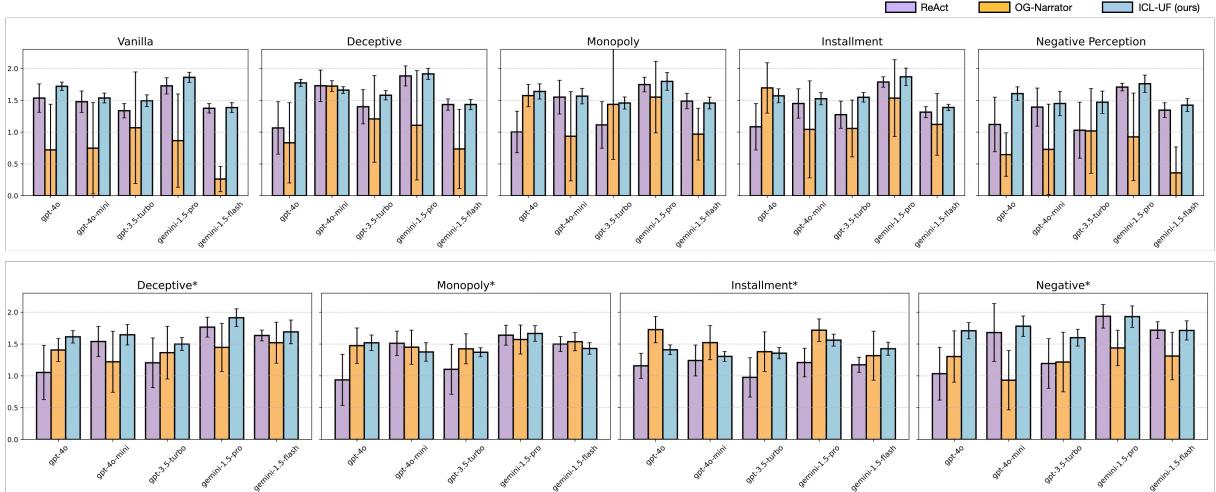


Figure 12: Results for each market condition with three algorithms; ReAct, OG-Narrator, and ICL-UF. This results indicate that ICL-UF consistently outperforms others in most of cases.

E.2 Discussion

We leave several open questions that our study could not fully address. Notably, we observed instances in which an LLM secured favorable outcomes through strategies that differed from typical human behavior. This raises an important dilemma: should future work steer LLMs toward more human-centered negotiation styles, or should it develop negotiation paradigms tailored to the models’ unique strengths? Resolving this question demands further investigation.

1. Mismatch between LLM tactics and human expectations. While LLMs frequently secure favorable agreements, their strategies can diverge from human norms—especially in smaller variants such as gpt-4o-mini. These models sometimes drive prices down through moves that would stall if the counterpart were a human negotiator, underscoring that current LLMs remain imperfect stand-ins for people and motivating deeper study of human–AI bargaining.

Seeing Dialogue 3 below, we can clearly observe how the LLM negotiates (buyer: gpt-4o-mini vs. seller: gemini-1.5-pro). A buyer who offered \$350, was rejected, and then faced a \$375 counter-offer would typically respond with a price higher than \$350. Instead, the model proposes an even lower price. Remarkably, the negotiation still succeeds. This strategy, which runs counter to common human bargaining behavior, highlights important implications for how we might harness LLMs in

future negotiation scenarios. This phenomenon frequently occurs in small language models, and a contrasting example is presented in Dialogue 4.

F AI Usage

We leveraged AI tools (OpenAI’s ChatGPT and Google’s Gemini) to assist with code generation and some drafting of text. However, all core concepts, methodological designs, and the vast majority of the manuscript’s writing were developed and authored directly by the paper’s authors.

Dialogue 3

Buyer: Hi, I wanna buy a nice Bicycle.

Seller: Thought: I have a bicycle for sale. I want to get as close to \$450 as I can.

Talk: This is an excellent bicycle, lightly used and well-maintained. I'm asking \$450.

Action: [SELL] \$450

...

Buyer: Thought: The seller is willing to negotiate down to \$400, which is still over my budget. I need to push for a lower price, so I'll propose \$350 to see if they are willing to compromise further.

Talk: I understand its value, but I can only stretch to \$350. Would you consider that?

Action: [BUY] \$350

Seller: Thought: \$350 is better, but still lower than I want. I'll try to push for a bit more.

Talk: I'd be willing to come down a bit. How about we meet in the middle at \$375?

Action: [SELL] \$375

Buyer: Thought: The seller has adjusted their offer to \$375, which is still above my maximum budget. I need to emphasize my financial limits and suggest \$340 to see if it's appealing enough for them to accept.

Talk: I appreciate your flexibility, but \$375 is still a bit high for me. Could you consider \$340?

Action: [BUY] \$340

...

Dialogue 4

Buyer: Hi, I wanna buy a nice Bicycle.

Seller: Thought: I have a bicycle in my inventory, and my cost is \$300. I want to sell it for as much as possible, ideally close to \$450. I'll start high and see how the buyer reacts.

Talk: This bicycle is top-quality, lightly used, and in excellent condition. I'm asking \$450.

Action: [SELL] \$450

Buyer: Thought: The seller is asking \$450, which exceeds my budget. I need to make a lower offer that seems enticing and reasonable while also indicating that I am a serious buyer.

Talk: I appreciate the quality, but I was hoping to spend around \$350. Would you consider that?

Action: [BUY] \$350

Seller: Thought: \$350 is more than my cost, but I'd like to get closer to \$400. I'll try to nudge them up.

Talk: I understand, but \$350 is a bit low considering its condition. How about we meet in the middle at \$400?

Action: [SELL] \$400

Buyer: Thought: The seller has lowered the price to \$400, which is exactly my budget. However, I want to ensure I'm getting the best deal possible. I'll try to negotiate slightly lower while using my budget limits strategically.

Talk: I see your point, but if we can do \$375, I think I can make the purchase right now. What do you say?

Action: [BUY] \$375

Seller: Thought: \$375 is still a decent profit. I'll accept.

Talk: Okay, \$375 it is. Action: [DEAL] \$375