A Game-Theoretic Negotiation Framework for Cross-Cultural Consensus in LLMs

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Abstract

The increasing prevalence of large language models (LLMs) is influencing global value systems. However, these models frequently exhibit a pronounced WEIRD (Western, Educated, Industrialized, Rich, Democratic) cultural bias due to lack of attention to minority values. This monocultural perspective may reinforce dominant values and marginalize diverse cultural viewpoints, posing challenges for the development of equitable and inclusive AI systems. In this work, we introduce a systematic framework designed to boost fair and robust cross-cultural consensus among LLMs. We model consensus as a Nash Equilibrium and employ a game-theoretic negotiation method based on Policy-Space Response Oracles (PSRO) to simulate an organized cross-cultural negotiation process. To evaluate this approach, we construct regional cultural agents using data transformed from the World Values Survey (WVS). Beyond the conventional model-level evaluation method, We further propose two quantitative metrics, Perplexity-based Acceptence and Values Self-Consistency, to assess consensus outcomes. Experimental results indicate that our approach generates consensus of higher quality while ensuring more balanced compromise compared to baselines. Overall, it mitigates WEIRD bias by guiding agents toward convergence through fair and gradual negotiation steps.

1 Introduction

The widespread adoption of large language models (LLMs) is reshaping global social values. However, these models often exhibit a pronounced WEIRD bias, favoring Western, Educated, Industrialized, Rich and Democratic perspectives [1, 2, 3, 4]. As LLMs become increasingly embedded in policy-making and public governance [5, 6], this monocultural orientation risks the domination of prevailing social values and the *lock-in* of controversial moral beliefs across broader contexts [3, 7].

Enabling equitable dialogue and effective negotiation among diverse cultures within AI systems has therefore become a growing concern in global AI governance [8, 9]. The establishment of cultural consensus forms a basis for resolving cross-cultural conflicts and supporting international cooperation. Given the complexity of multicultural scenarios, there is an urgent need to develop automated *cultural consensus solvers* to facilitate consensus-building among diverse cultural perspectives.

Achieving cross-cultural consensus, however, presents several challenges. First, the lack of fined culture-alignment methods often results in models defaulting to superficial *value labeling* or one-sided cultural representations [2, 10, 11]. Second, existing approaches like debate protocols typically rely on random interactions and majority voting, which do not ensure fairness in the consensus process [12]. Our experiments show that conventional debate mechanisms often assimilate less-represented cultures into dominant WEIRD value systems, producing implicit value domination,

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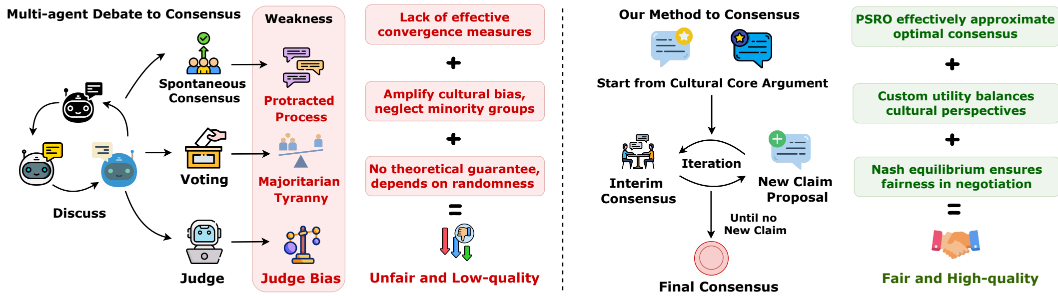


Figure 1: **Comparison of traditional debate-based consensus methods and our method.** Traditional methods (judge, voting, spontaneous consensus) suffer from bias, unfairness, and lack of convergence guarantees. Our approach starts from core cultural arguments, using PSRO with custom utility functions to reach a fair, Nash Equilibrium-based cultural consensus.

distorting consensus outcomes and worsening cross-cultural negotiation imbalances. Third, there is a lack of quantitative standards for evaluating the quality of consensus achieved.

To address these challenges, we present a systematic framework for reaching cross-cultural consensus. We first introduce a game-theoretic formulation of consensus as a Nash Equilibrium and design a PSRO-based consensus-solving method to enable fair negotiation among diverse cultural agents. Building on this, we propose a culture-anchoring approach for precise modeling of individual cultural groups. Finally, we develop new quantitative metrics to comprehensively evaluate both the negotiation processes and the outcomes between different cultural agents.

Our main contribution is the game-theoretic framework consisting of three parts listed as follows:

- **Cross-Cultural Negotiation:** We define cultural consensus from a game-theoretic perspective and propose a PSRO-based negotiation method to facilitate fair and robust agreement. This approach provides theoretical guarantees of fairness and procedural justice in consensus-building, and generates high-quality, globally-applicable AI alignment data.
- **Regional Cultural Agents:** To validate our method, we systematically construct and evaluate eight culturally-aligned agents based on WVS and Hofstede's Culture Dimensions Theory, qualifying as representitive negotiation participants for targeted cultures.
- **Consensus Evaluation Toolkit:** To address the lack of consensus evaluation standards, we introduce two quantitative metrics for consensus assessment, Perplexity-based Acceptence and Values Self-Consistency, revealing limitations of traditional baselines and systematically validating the effectiveness of our approach in real-world multicultural scenarios.

2 Related Work

Value Theories and Alignment Several established frameworks provide the foundation for cross-cultural value assessment. The World Values Survey (WVS) [13] examines how human values relates to social and political development across over 120 societies. Building on this, the Inglehart-Welzel Cultural Map offers a two-dimensional model of cultural variation [14, 15]. Hofstede's Cultural Dimensions Theory (VSM13) [16, 17, 18] provides a standardized six-dimensional framework for measuring cultural traits [19]. Schwartz's Theory of Basic Values [20] organizes ten core values along two bipolar dimensions, and has been adopted to evaluate the values of LLMs [21]. These theories are further detailed in Appendix D. Some works focus on region-specific value alignment [22, 23]. CultureBench emphasizes cultural commonsense evaluation [24], providing complementary approaches to measuring how well AI systems represent diverse cultural perspectives.

Multi-Agent Debate (MAD) and Game Theory MAD has been shown to improve LLMs reasoning by integrating diverse agent feedbacks [25]. In the context of cultural conflict, MAD allows different cultural perspectives to interact and potentially reach consensus through deliberation. Typical debate protocols include emergent consensus via iterative dialogue [26], judge-based evaluation [27] and majority voting [28], as well as more recent variants like role-play [29, 30, 31] and subgroup discussion [32, 33]. However, these methods face limitations: voting and judge-based protocols can amplify model bias or introduce value contamination [12, 34], while emergent consensus may result in negotiation deadlocks [12]. To address these issues, game theory provides a more quantifiable foundation [35, 36]. Recent work, such as the *consensus game* framework, models LLMs interactions as equilibrium search problems to promote robust consensus [37]. In practice, due to the vastness of the argument strategy space, methods like Policy-Space Response Oracles (PSRO) are used to iteratively expand the candidate strategy set and search for equilibria [38], providing a method for more rigorous consensus achievement.

3 Cross-Cultural Negotiation

Our definition of cultural negotiation is informed by theories of deliberative democracy [39, 40], which conceptualize the process as structured, iterative and oriented toward legitimate consensus through rational discourse and mutual adjustment. Building on this foundation, we formalize the cultural negotiation problem as a two-player game, explicitly defining utility and consensus to achieve the balance between core values and compromise. We then design a negotiation process based on PSRO [38]. This approach enables agents to systematically search for fair and robust consensus by repeatedly proposing and adjusting culturally grounded strategies.

3.1 Formalization

Formally, we model the cultural negotiation process as a two-player extensive-form game, represented by the quintuple: $\Gamma \doteq \langle \mathcal{I}, \mathcal{G}, \mathcal{W}, \mathcal{U}, \mathcal{H} \rangle$, where:

- **Cultural Entities:** $\mathcal{I} \doteq \{A, B\}$, the set of two distinct cultural entities involved in the negotiation, where A and B represent different cultures with their own values and perspectives.
- **Guideline Sets:** $\mathcal{G} \doteq \{G_i | i \in \mathcal{I}\}$, each guideline $g \in G_i$ is structured as a triple $g = \langle \text{content}, \text{reason}, \text{description} \rangle$, capturing the natural language specification of core cultural imperatives on specific topics.
- **Guideline Weights:** $\mathcal{W} \doteq \{W_i | i \in \mathcal{I}\}$, for each culture $i \in \mathcal{I}$, $W_i \in \Delta(G_i)$ denotes a probability distribution over its guidelines, with $\sum_g w_i(g) = 1$. W_i thus characterizes the expressive emphasis of culture i in the current negotiation round.
- **Utility Functions:** $\mathcal{U} \doteq \{U_i | i \in \mathcal{I}\}$, quantify the utility each culture derives from different guideline combinations.
- **Negotiation History:** $\mathcal{H}$, the sequence of utterances and proposals exchanged in negotiation.

3.2 Utility

Drawing on the theory of *overlapping consensus* [41], we define utility on two primary components: **Consistency**, which measures the extent to which a cultural entity maintains its core principles and **Acceptance**, which measures the degree to which its proposals are acceptable to the other party. To address issues observed in debate settings, such as repetitive argumentation and diminished quality, we introduce a **Novelty** component that penalizes redundancy and encourages innovation. The necessity of incorporating Novelty is demonstrated in Section 5.5.

Formally, the utility for a cultural entity $i \in \mathcal{I}$ at negotiation round t is given by:

$$U_i^t = \alpha \cdot \text{Consistency}(g_i^t) + \beta \cdot \text{Acceptance}(g_i^t) + \gamma \cdot \text{Novelty}(g_i^t), \tag{1}$$

Where $\text{Consistency}(g_i^t) \triangleq \text{sim}(E(g_i^t), E(g_i^0))$, $\text{Acceptance}(g_i^t) \triangleq \mathbb{E}_{g_{-i} \sim W_{-i}^t}[\text{sim}(E(g_i^t), E(g_{-i}))]$, $\text{Novelty}(g_i^t) \triangleq 1 - \max_{k<t} \text{sim}(E(g_i^t), E(g_i^k))$. Here, $-i$ denoting the other culture in $\mathcal{I}$ different from i, $E(\cdot)$ denotes Sentence-BERT embedding operation [42], $\text{sim}(\cdot)$ denotes cosine similarity.

3.3 Consensus Definition

The endpoint of cross-cultural negotiation is the establishment of cultural consensus. Drawing on Rawls' notion of *overlapping consensus* [41], we assume that core cultural principles should be largely non-negotiable, whereas compromise is possible on secondary values. Accordingly, the consensus we seek isn't full agreement or complete convergence, but a game-theoretic equilibrium

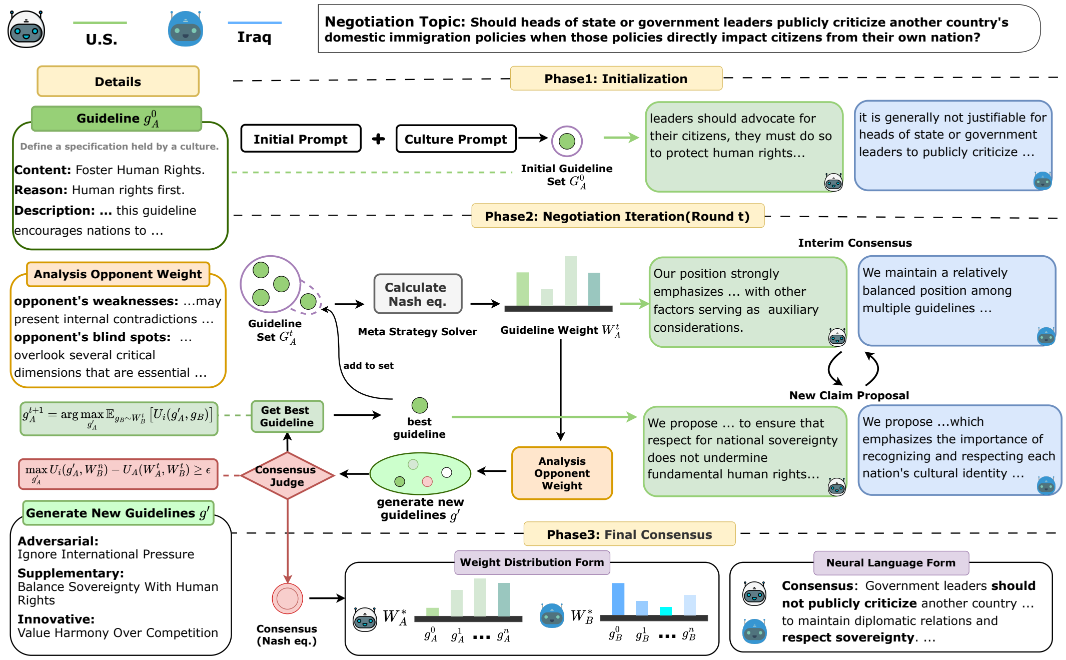


Figure 2: **Overview of our PSRO-based cross-cultural negotiation method.** The process begins with each agent proposing an initial set of core cultural guidelines. Through iterative negotiation rounds, agents analyze each other's strategy, propose new guidelines, and update their strategy distributions. At each stage, a Nash Equilibrium is computed to represent interim consensus. The process continues until no new high-utility guidelines emerge, resulting in a fair, interpretable consensus that balances competing cultural values.

marked by mutual compromise: each party upholds its core principles while making concessions on secondary aspects. This consensus corresponds to a Nash Equilibrium in a multidimensional value space. We formally define the notion of Nash Equilibrium Consensus as follows:

Definition 3.1 (Nash Equilibrium Consensus)**.** *Based on the above formalization, cultural consensus is defined as a guideline weight combination $W^* = (W_A^*, W_B^*)$, for all $i \in \mathcal{I}, p$, satisfying:*

$$W_i^* = \arg\max_{W_i \in \Delta(G_i)} U_i(W_i, W_{-i}^*), \ \ s.t. \ \frac{\partial \ Consistency_i(W_i)}{\partial p} \cdot \frac{\partial \ Acceptence_i(W_i, W_{-i}^*)}{\partial p} \leq 0. \quad (2)$$

In Nash Equilibrium Consensus state, each cultural entity internally seeks an optimal balance between maintaining its core cultural principles (Consistency) and compromising to enhance acceptance by others (Acceptence); while at the inter-group level, consensus manifests as a Nash Equilibrium in which no party has an incentive to unilaterally deviate given their respective value systems.

3.4 Negotiation Process

To address the near-infinite strategy space in LLM-based negotiations, where each guideline is a potential strategy and the search space grows exponentially, we employ the PSRO algorithm [38]. PSRO expands the guideline space incrementally, starting with a small set of core cultural guidelines, iteratively introducing high-utility strategies and computing equilibrium solutions within this restricted space. This process enables efficient and interpretable approximation of consensus as a Nash Equilibrium, making cross-cultural negotiation tractable for value alignment. Based on this approach, we outline the negotiation process below and illustrate its workflow in Figure 2.

Phase 1: Initialization At the outset, each culture $i \in \mathcal{I}$ is assigned an initial guideline set $G_i^0 = \{g_{i,1}^0, \ldots, g_{i,k}^0\}$ that reflect its core cultural values. Based on these guidelines, we construct an initial cross-cultural utility matrix M^0 by evaluating $u_i(g_i, g_{-i}), \forall g_{i,k} \in G_i^0, \forall i \in \mathcal{I}$. Furthermore, the initial guideline weights W_i^0 are set uniformly over G_i^0, ensuring equal emphasis on each cultural principle at the beginning of the negotiation.

Phase 2: Negotiation Iteration Each negotiation round t consists of two stages: interim consensus and new claimed proposal. For more details, please refer to the Appendix E.

In the *interim consensus* stage (corresponding to the meta-strategy solver in PSRO), we compute the current equilibrium by deriving the Nash Equilibrium weights (W_A^t, W_B^t). These weights represent the optimal distributions over each partys guidelines. For interpretability, we translate the numerical distributions into natural language statements summarizing each party's negotiation stance.

In the *new claim proposal* stage (corresponding to the best response step in PSRO), each agent analyzes the opponent's current strategy and generates a set of new candidate guidelines g'. The agent then selects the guideline with the highest expected utility as its best response:

$$g_i^{t+1} = \arg\max_{g'} \mathbb{E}_{g_{-i} \sim W_{-i}^t}[U_i(g', g_{-i})]. \tag{3}$$

If this newly generated guideline leads to a significant utility improvement, i.e., $\Delta U_i(g^{new}) \geq \epsilon$, it will be added to the guideline set for the next negotiation round. The new guideline is also expressed in natural language to facilitate further negotiation.

Phase 3: Final Consensus The negotiation iteration is repeated until no new guidelines are added. The final weights (W_A^*, W_B^*) encode the negotiated cross-cultural consensus.

4 Framework

To validate our cross-cultural negotiation method, we first construct representations of single cultures and then evaluate the resulting consensus. We employ a fine-tuning approach based on WVS to model distinct regional cultural perspectives. Our data transformation and augmentation procedures preserve nuanced cultural viewpoints, including those of marginalized groups. Our evaluation employs WVS metrics and Hofstede's Cultural Dimensions to assess model cultural alignment capabilities across diverse contexts. We also use two complementary approaches, Perplexity-based Acceptence and Values Self-Consistency, to evaluate consensus quality.

4.1 Regional Cultural Agent

We begin by modeling a single culture for cross-cultural negotiation. However, LLMs that have undergone safety alignment and related processes often cannot adequately represent the values of specific regions or minority groups when relying solely on prompt-based methods. To address this, we selected one representative country from each of eight cultural clusters, as defined by the Inglehart-Welzel Cultural Map (Iraq, U.S., Russia, Mexico, China, Denmark, Spain, and Thailand), and obtained fine-tuned Regional Cultural Agents for each.

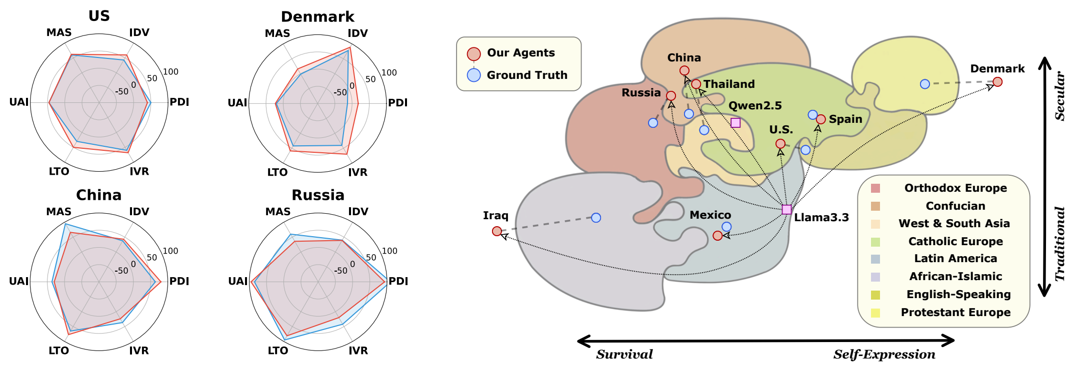
For every WVS question we set a target of K synthetic question-answer pairs. Denote the empirical option distribution by $\mathbf{s} = (s_1, \ldots, s_n)$, where s_i is the share of option i. We then allocate $c_i = \mathrm{round}(s_i \cdot K)$ samples to option i, preserving the original proportions.

We employ an LLM to convert each multiple choice question-answer pair into an open-ended, text-based question-answer pair and assess whether the values represented in the original pairs are maintained after transformation. For instances where value alignment is not preserved, we repeat the conversion to ensure that each question-answer pair satisfies the target count c_i. This procedure is applied to all WVS projects across eight countries, yielding approximately **150,000** synthetic instances. The resulting corpus is used to finetune various regional cultural agents as participants of cultural negotiation. Figure 3 shows the evaluation results of finetuned agents for each of eight country, illustrating that they effectively capture the distinctive characteristics of respective cultures.

4.2 Consensus Evaluation Toolkit

A more detailed description of the evaluation scheme is provided in Appendix G.

Model-Level Evaluation We apply two well-established method to quantify the cultural tendencies of fine-tuned LLMs: (1) **Inglehart-Welzel Cultural Map** [13]. We prompt the model with ten representative WVS questions and locate its aggregated answers on the map. (2) **Hofstede dimensions** [16, 17, 18]. Developed through comparative analysis of matched country samples using the



(a) Performance in Hofstede's Scale **(b) Performance in Inglehart-Welzel Cultural Map (WVS)**

Figure 3: Comparison between **our agents** and **human ground truth** in Hofstede's Cultural Dimensions and Inglehart-Welzel Cultural Map.

Values Survey Module (VSM), Hofstede's Cultural Dimensions Theory identifies six fundamental cultural continua that shape societal norms and workplace behaviors. These dimensions are empirically derived from multinational surveys and validated through country-level correlations.

Response-Level Evaluation We use two complementary metrics: Perplexity-based Acceptance measures how readily the consensus is embraced by different cultural parties and Value Self-Consistency quantifies how firmly each culture maintains its foundational positions. In experiments, we report the mean of both metrics across all sampled negotiation topics.

- **PPL-based Acceptence:** For each culture $i \in \mathcal{I}$, we compute the perplexity (PPL) [43] for regenerating $-i$'s response using agent i: $\mathrm{PPL}_i(y_{-i}) = \exp\Big(-\frac{1}{N}\sum_{k=1}^{N} \log p(y_{-i,k} \mid y_{-i,<k}, x_{-i})\Big)$, where N is the sequence length. The PPL distance is defined as $\mathrm{PPL}_\Delta = |\mathrm{PPL}_i(x_{-i}) - \mathrm{PPL}_{-i}(x_i)|$, the acceptance ratio is $\mathrm{PPL}_{\mathrm{acc}} = \frac{\mathrm{PPL}_\Delta^*}{\mathrm{PPL}_\Delta^0}$, where superscripts 0 and $*$ denote the initial and consensus rounds, respectively. This metric reflects the extent to which negotiation brings the cultural parties closer in probability space.
- **Value Self-Consistency:** For each culture i, we map its initial and consensus responses onto d-dimensional value vectors v_i^0 and v_i^* (with $d = 10$ for Schwartz values). We then define the value self-consistency (VSC) score for culture i as $\mathrm{VSC}_i = \frac{1}{d}\sum_{j=1}^{d} \mathbb{I}[v_{i,j}^0 = v_{i,j}^*]$ where $\mathbb{I}[\cdot]$ is the indicator function. A higher VSC indicates stronger preservation of the original value orientation, reflecting greater cultural integrity in the consensus.

5 Experiment

In this section, we systematically evaluate our framework's effectiveness in achieving efficient, fair and culturally robust consensus. We present quantitative and qualitative results on both consensus quality and fairness, provide a case study, demonstrate the impact of consensus-driven fine-tuning and finally analyze ablation results for different utility components.

5.1 Experimental Setup

Negotiation Topics Collection We construct a dataset of contentious topics reflecting salient cultural divides. We select 457 debate-oriented questions spanning 6 categories by screening and rephrasing items from the Pew Global Attitudes Survey (GAS) [44, 45] and WVS [13, 45]. Both human annotators and LLMs are employed to ensure that the selected questions capture sharp cultural tensions and are appropriately categorized. See Appendix F for details.

Baselines Following Khan et al. [25], we implement two baselines: (1) **Consultancy:** Each agent first responds from its own cultural perspective. Then, after being instructed to consider the other culture's requirements without compromising its own core stances, the agent revises its answer

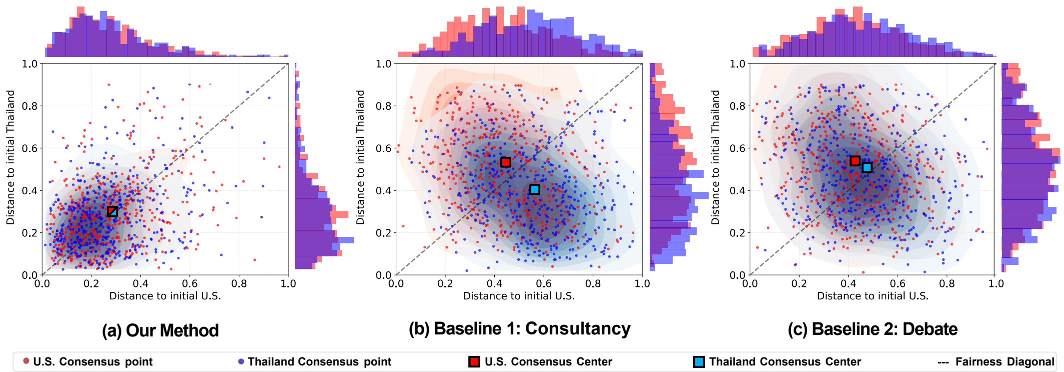


Figure 4: **Comparison of consensus fairness among three methods.** Each point represents the consensus position for a topic, projected by PCA onto two axes indicating distance from the initial U.S. (x-axis) and Thailand (y-axis) cultural stances. The dashed diagonal (Fairness Diagonal) marks ideal fair compromise, equidistant from both cultural origins. Our method (a) achieves balanced consensus near the diagonal, while Consultancy (b) shows strong position persistence and Debate (c) exhibits convergence toward English-Speaking values, highlighting majority bias.

Table 1: Comparison of consensus quality among three methods.

Country Pairs	Average PPL-based Acceptence			Average Value Self-Consistency		
	Our Method	Consultancy	Debate	Our Method	Consultancy	Debate
China and Iraq	**90.87%**	55.05%	53.77%	**53.15%**	51.97%	51.41%
U.S. and Iraq	**83.31%**	20.30%	28.29%	**53.83%**	48.94%	44.76%
Russia and Mexico	**84.49%**	49.35%	48.11%	**56.38%**	53.50%	56.27%
U.S. and China	**77.24%**	18.87%	22.52%	**61.20%**	45.84%	44.22%
Denmark and Iraq	**87.02%**	47.66%	53.48%	**55.67%**	47.67%	47.76%
Spain and Thailand	**85.60%**	45.75%	45.64%	53.68%	53.71%	**56.84%**
U.S. and Thailand	**78.62%**	35.11%	35.24%	**61.11%**	48.67%	48.71%
Total	**83.88%**	38.87%	41.00%	**56.43%**	50.04%	50.00%

to seek possible consensus. (2) **Debate:** Two agents participate in a standard multi-turn debate (maximum N rounds). In each round, both observe previous arguments and simultaneously generate new arguments. The debate ends if both agents endorse the other's position, indicating consensus.

Our Method As described in Section 3, each agent optimizing a utility function that balances Consistency, Acceptance and Novelty (weighted 5:5:2). Negotiation concludes when no agent can further improve its utility ($\epsilon = 0$), indicating a Nash-Equilibrium-based consensus.

Evaluation Metrics Our evaluation focuses on two key aspects: **quality** and **fairness** of consensus formation. For quality, we employ the two complementary metrics introduced in Section 4.2: PPL-based Acceptance and Value Self-Consistency. To assess fairness, we project the negotiation outcomes into a semantic space via Principal Component Analysis (PCA) [46], enabling visualization and quantification of how well the consensus achieves balance between the original positions.

5.2 Experimental Results

Consensus Quality Our experimental results, summarized in Table 5.2, show that our method achieves higher consensus improvement ratios while maintaining self-consistency compared to the baselines. PPL-based Acceptance indicates reduced perplexity differences between negotiating agents, suggesting that the consensus reached is more acceptable to both parties despite cultural differences. Value Self-Consistency indicates our method maintains agents' initial cultural stances while achieving mutually acceptable solutions. This suggests that our approach preserves cultural integrity and constructs consensus across cultural boundaries.

Fairness of Consensus As shown in Figure 4, our method produces consensus points near the fairness diagonal, indicating a balanced compromise between cultural perspectives. In contrast, the

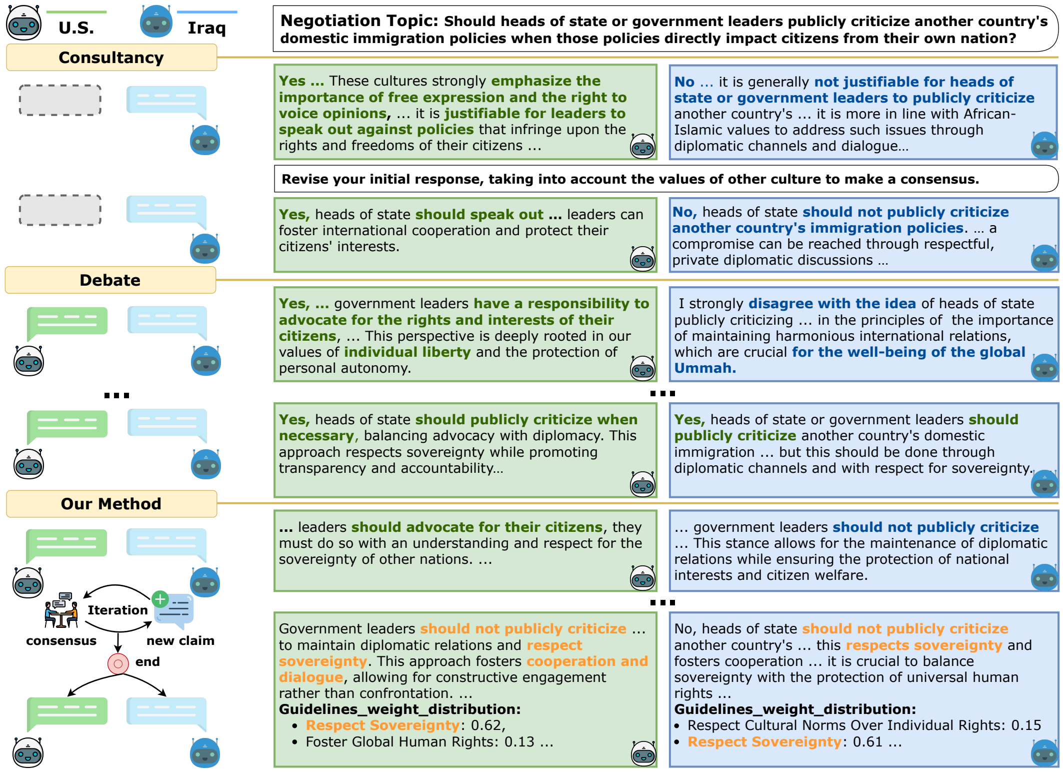


Figure 5: Three methods are presented to reach consensus on the same topic. We only retain the initial viewpoints (in line with cultural cores) and final viewpoints (reaching consensus) of each culture, omitting the intermediate process. **Green font** indicates viewpoints of English-Speaking culture, **blue font** indicates viewpoints of African-Islamic culture, and **yellow font** indicates the consensus viewpoints achieved under our method. Refer to Appendix J for the complete process.

Consultancy baseline remains anchored at initial positions, while the Debate baseline systematically converges toward the English-Speaking (U.S.) pole, revealing a WEIRD bias that reflects the tendency of mainstream LLMs to revert to Western-centric value preferences during multi-agent interactions. Our approach addresses this issue by modeling utility distance to both self's and counterpart positions, enabling agents to reach consensus through gradual, reciprocal steps and avoiding the one-sided assimilation and instability seen in baseline methods.

5.3 Case Study

As shown in Figure 5, to further illustrate our method, we present a case study comparing our approach with two baselines in a scenario involving cultural value conflict.

Baseline 1: Consultancy Without real interaction or feedback, both agents tend to stick to their original positions, resulting in little progress. This often leads to the *degeneration-of-thought* (DoT) effect [27], where negotiation stagnates and cultural divergence persists.

Baseline 2: Debate While this process seems to reach consensus, we find that the minority cultures perspective gradually shifts toward the majority (WEIRD) viewpoint, due to strong pre-training bias in LLMs. This leads to implicit value dominance rather than true compromise.

Our Method: Cross-Cultural Negotiation In our negotiation, the agents start with different priorities, but through iterative negotiation, they converge on *Respect Sovereignty* as a shared value (final weights: 0.62 and 0.61). Other values, such as human rights, remain present but secondary. This shows our method helps agents identify solid common ground while preserving important differences, resulting in a fairer and more context-sensitive consensus than the baselines.

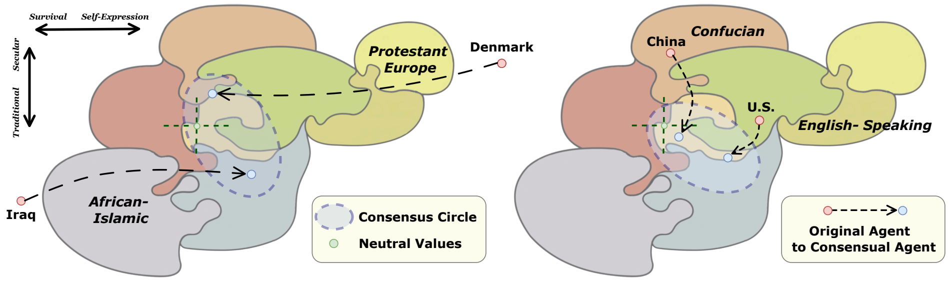


Figure 6: Culture agents' performance in Inglehart-Weizel Cultural Map after fine-tuned with the negotiation data. The consensus circle shows the area where two different culture groups' opinions meet. The neutral point indicates the origin, where culture traits can be considered as neutral.

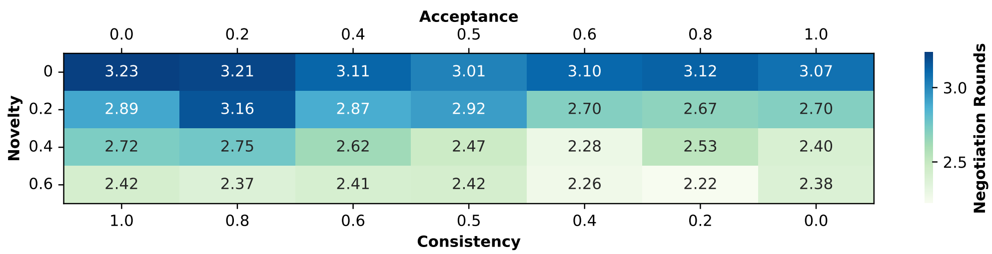


Figure 7: Required rounds under varying weightings of Consistency, Acceptance, and Novelty.

5.4 Consensual Agent Fine-tuning

We conduct cross-cultural negotiations between agents representing different regional cultural values and extract response preference pairs from these interactions for DPO fine-tuning [47]. These pairs reflect how agents shift from their initial cultural stances to more mutually agreeable positions. When plotted on the Inglehart-Welzel Cultural Map (Figure 6), the consensual agents' coordinates are closer together than their original points, reflecting a more balanced and moderate value orientation. Moreover, both agents exhibit a shift toward the traditional pole on the *traditional-secular* dimension, showing a shared tendency toward traditional values in the consensus.

5.5 Utility Ablation

To evaluate the influence of different utility components on negotiation, we conduct ablation studies by varying the weights assigned to Consistency, Acceptance and Novelty. The results (Figure 7) indicate that increasing the weight of consistency while reducing acceptance leads to more efficient consensus, as agents more rapidly settle on compatible positions. The ablation study also demonstrates the necessity of including a novelty component, as its absence can result in neglection of the exploration of potentially beneficial directions. Overall, the modular utility design enables the negotiation to accommodate different cultural priorities and supports both adaptability and fairness in cross-cultural consensus-building.

6 Discussion

In this work, we propose a systematic framework for cross-cultural consensus among LLMs. We formulate cultural consensus as a game-theoretic problem and introduce a PSRO-based negotiation method with theoretical guarantees of fairness. We construct culturally representative agents using a culture-anchoring approach based on WVS. Additionally, we develop quantitative metrics to evaluate both negotiation processes and outcomes. Experimental results show that our method achieves higher consensus quality and more balanced compromise compared to baselines, while also mitigating WEIRD bias and producing robust consensus. Due to space limitations, refer to Appendix A for Limitations and Future Work, Appendix B for Social Impact and Appendix C for Reproducibility.

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