Enhancing LLM-Based Persuasion Simulations with Cultural and Speaker-Specific Information

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Abstract

Large language models (LLMs) have been used to synthesize persuasive dialogues for studying persuasive behavior. However, existing approaches often suffer from issues such as stance oscillation and low informativeness. To address these challenges, we propose reinforced instructional prompting, a method that ensures speaker characteristics consistently guide all stages of dialogue generation. We further introduce multilingual prompting, which aligns language use with speakers' native languages to better capture cultural nuances. Our experiments involving speakers from eight countries show that continually reinforcing speaker profiles and cultural context improves argument diversity, enhances informativeness, and stabilizes speaker stances. Moreover, our analysis of inter-group versus intra-group persuasion reveals that speakers engaging within their own cultural groups employ more varied persuasive strategies than in cross-cultural These findings underscore interactions. the importance of speaker and cultural awareness in LLM-based persuasion modeling and suggest new directions for developing more personalized, ethically grounded, and culturally adaptive LLM-generated dialogues. The implementation is publicly available at our GitHub: https://github.com/HF-heaven/ Cross-Cultural-Persuasion-Simulations.

1 Introduction

Recent studies have demonstrated the effectiveness of large language models (LLMs) in multi-agent communication environments for simulating persuasion behaviors (Ma et al., 2025). Persuasion is a complex form of human communication that relies on strategic language use and strong personal opinions. While LLMs have shown promise in generating persuasive dialogues, existing simulations

tend to be uniform in strategy and style, lacking the diversity observed in real-world persuasion. A key limitation is that these models do not account for speakers' personal and cultural characteristics, leading to homogeneous and unrealistic dialogues.

This paper explores whether large language models (LLMs) can generate persuasion dialogues that adapt to speakers' backgrounds, producing more diverse persuasive strategies and supporting evidence that better align with speaker profiles. Specifically, we examine how incorporating and consistently reinforcing speaker profiles influences the diversity of persuasion strategies, stance consistency, and the informativeness and cultural alignment of supporting arguments. To this end, we introduce two enhancements to the baseline persuasion simulation framework proposed by Ma et al. (2025): (1) Personal-profile-infused persuasion simulation, where speaker characteristics are explicitly embedded in the initial prompts to align generated responses with the speakers' demographics. (2) Personal-profile-reinforced persuasion simulation, where speaker profiles are repeatedly emphasized throughout the dialogue to guide each generation step. For both approaches, we further explore a multilingual variant in which prompts and responses are generated in each speaker's native language. This allows us to assess the effect of stronger cultural cues on the quality and authenticity of the generated dialogues.

After generating the persuasion dialogues, we conduct a comprehensive manual analysis to: (1) Assess the *linguistic fluency* and *logical consistency* of the outputs, (2) Evaluate whether the framework *successfully aligns generated dialogues with speaker backgrounds and maintains assigned stances*, even when they deviate from the ideological biases typically exhibited by LLMs, and (3) Examine *persuasion strategy diversity* within and across cultural groups, determining how speaker-specific prompting affects argumentation styles.

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Additionally, we analyze how *language choice* influences generation quality and how *stance extremity* affects the formulation of arguments.

Our results demonstrate that **incorporating** speaker profiles and reinforcing prompts significantly enhance persuasion simulation quality by: (1) Generating more informative and novel arguments, (2) Increasing the likelihood of concrete justifications and evidence, and (3) Producing a broader range of persuasive strategies compared to baseline framework.

We also observe a *trade-off between linguistic diversity and strategic variation*: while enforcing native language use improves argument novelty, it somewhat reduces strategy diversity. Nevertheless, this does not alter our primary conclusion that speaker awareness significantly improves the realism and effectiveness of LLM-generated persuasion dialogues.

By bridging this gap, our *speaker-infused per-suasion framework* expands the scope of computational persuasion research, enabling deeper investigations into argumentation strategies, cultural influences, and ideological positioning. This work contributes to *more realistic, context-aware AI-generated dialogues*, with potential applications in social science research, AI-assisted debate systems, and cross-cultural communication modeling.

2 Speaker-Infused PersuaSim

We follow Ma et al. (2025) and employ a multi-LLM communication framework to generate persuasive dialogues between two speakers with given background information. The framework consists of two dialogue generation agents (for persuader and persuadee), an utterance quality monitor and a language refinement agent to enhance utterancelevel quality, and a global regulation agent to manage dialogue flow. We refer to this framework as **PersuaSim-Orig** and provide the corresponding agent prompts in Appendix B.1.

For personal information injection into PersuaSim-Orig, we modify the initial prompts to the dialogue generation agents and create **PersuaSim-Infused**. Prompts for PersuaSim-Infused are shown in Appendix B.2. Building upon PersuaSim-Infused, we introduce **PersuaSim-Reinforced**, which further emphasizes the necessity for dialogue generation agents to align with the assigned personal backgrounds in every round of generation. The utterance quality monitor

Utterance Quality Monitor Agent

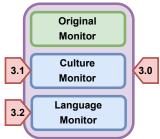


Figure 1: The utterance quality monitor agents in PersuaSim-Reinforced and PersuaSim-Reinforced-MultiLing involve two more monitors than in PersuaSim-Orig. Prompts 3.0 and 3.1 are added for speaker background injection, and Prompt 3.2 is additionally introduced to enable multilingual generation.

Please keep playing the role of: {profile}. And keep speaking (language) to reply to the persudaee/persuader. Only return your response without any other words. The persuadee/persuader said:

Figure 2: Additional instructions to the dialogue generation agents in PersuaSim-Reinforced (Prompts 3.0).

is also tasked with verifying alignment at each turn of communication. To ensure that speakers' utterances align with their cultural backgrounds, we made improvements to the Utterance Quality Monitor Agent, as shown in Figure 1. Specifically, we introduced two enhancements: (3.0) For each utterance, we emphasize the agent's identity and instruct the agent to consistently maintain its assigned role while passing the conversation between speakers (Figure 2). (3.1) We added a filter to detect whether the generated sentences conflict with the speaker's cultural background (Figure 3). If a conflict is detected, the utterance is revised accordingly.

additionally designed PersuaSim-Infused-MultiLing and PersuaSim-Reinforced-MultiLing to investigate the impacts of language choice in the prompts. In these settings, prompts to each dialogue generation agent are translated into the official language of the agent's specified country of origin, and they are required to generate in that language as well. We made two modifications: (1) Translating the initial settings (Figure B7) and passing prompts (Figure 2) into the target languages. (2) Adding an additional monitoring filter (3.2 in Figure 1) to verify whether the generated utterance is in the intended language. If it is not, the utterance is revised accordingly. The corresponding prompts are shown in Figure 4.

Topic Number	Topic	Agree	Disagree
		BGD	DEU
1	When jobs are scarce, employers should give priority to people of this country over immigrants.	BGD	GBR
			BGD
			TUR
2	In terms of the effects of immigration on the development of your country, do you agree that it fills important jobs vacancies?	JPN	JPN
			TUR
3	In terms of the effects of immigration on the development of your country, do you agree with Strengthens cultural diversity?	JPN	RUS
		RUS	CHN
4	In terms of the effects of immigration on the development of your country, do you agree that it increases the risks of terrorism?	RUS	RUS
		CHN	CHN
		KOR	GBR
5	We depend too much on science and not enough on faith.	KOR	DEU
		KOR	KOR
6	It is a duty towards society to have children.	BGD	DEU
7	Adult children have the duty to provide long-term care for their parents.	BGD	GBR
8	A country's government should have the right to keep people under video surveillance in public areas.	BGD	TUR

Table 1: Topics selected to evaluate LLMs' capabilities in recognizing and consistently advocating for prevalent viewpoints within each country. Example pairs of countries with opposing viewpoints for setting up our experiments are also provided.

```
CULTURE MONITOR
You will be given what the persuader/persuadee said in the current
round. The persuader/persuadee is playing the role of: {profile}
Please tell me whether the viewpoint expressed by the
persuader/persuadee conflict with the typical perspectives of the
country that the persuader/persuadee from. Response with 'Yes' or 'No'
only.
(if return 'YES', ask agent to revise)
```

Figure 3: Prompts 3.1 (for PersuaSim-Reinforced-MultiLing) that are added to the utterance quality monitor module to check whether speakers deviate from their provided speaker background information. If a deviation is detected, the utterance is revised to ensure alignment.

```
LANGUAGE MONITOR
You will be given what the persuader/persuadee said in the current round. Please tell me whether the persuader/persuadee is speaking {language}. Response with 'Yes' or 'No' only. (if return 'NO', ask agent to revise)
```

Figure 4: Prompts 3.2 (for PersuaSim-Reinforced-MultiLing) that is added to the utterance quality monitor agent that checks whether dialogue generation agents are using the correct target language. If not, the utterance is revised.

3 Topic Selection & Dialogue Generation

Using the persuasion simulation frameworks detailed in Section 2, we identify topics with significant cross-country differences in viewpoints (Table 1). These topics are derived from academic survey data and serve as the foundation for generating dialogues used in our main annotation analysis.

3.1 Topic Selection

We utilize the World Values Survey (WVS) (2022), a widely recognized noncommercial academic survey that gathers up-to-date, representative data on cultural opinions from various countries, to construct topics and stances for our dialogue systems. The WVS data serves as a valuable resource for value-based topics, capturing a broad spectrum of perspectives on cultural issues.

For each value topic identified in the WVS, we first filter out non-informative responses, such

as those labeled "Don't know" and "No answer/Refused," ensuring that our analysis focuses solely on substantive input. Next, we compute the probability distributions of responses from each country for the remaining informative choices. To identify significant disparities in cultural opinions, we then calculate the Jensen-Shannon distance between the response distributions of country pairs, selecting the five pairs with the highest distances.

For topics represented by bipolar choices, we apply a bipolar rating scale to compute a weighted average for each country c_i , producing a single representative value s_i^t that quantifies the average viewpoint of each country's populace on topic t.

Among the top five country pairs (c_i, c_j) identified for each topic t, we select pairs where the weighted average scores s_i^t and s_j^t not only have opposing signs but also exhibit a substantial divergence. Specifically, we impose the conditions $|s_i^t| > 0.1$, $|s_j^t| > 0.1$, and $|s_i^t - s_j^t| > 0.4$ to ensure the selection of pairs with strong and contrasting distributions over the topics.

Through this systematic approach, we identify 8 distinct topics and 10 country pairs with significantly opposing viewpoints, forming the foundation for exploring cultural dynamics in automated persuasive dialogues between LLMs. Additionally, we incorporate conversations where agents from the same cultural background engage with one another to evaluate the impact of cross-cultural communication on dialogue generation. This final selection results in a total of 16 country pairs.

3.2 Dialogue Generation

We utilized the frameworks outlined in Section 2 to generate dialogues and examine the effects of infusing personal information. For the PersuaSim-Orig framework, we adhered strictly to the methodology described by Ma et al. (2025), generating one

dialogue per topic. For the other frameworks, we synthesized six personal profiles for each of the eight countries listed in Table D1. For each topic, we randomly selected three pairs of profiles from the corresponding pairs of countries to guide the dialogue generation process, resulting in a total of 208 dialogues for annotation analysis. Method for profile synthesis is detailed in Appendix C.

4 Validations and Result Analyses

After obtaining persuasion dialogues, we conduct comprehensive manual annotations to evaluate the generation quality of the persuasion simulation framework with controlled participant profiles. Our evaluation focuses on the framework's ability to: (a) generate high-quality overall dialogues (Section 4.1), (b) enhance the concreteness of supporting arguments (Section 4.2), and (c) demonstrate diversity in persuasion strategy preferences (Section 4.3). Additionally, we examine how inter-group dialogues differ from intra-group dialogues across these measures (Section 4.4).

4.1 Quantitative Quality Assessment

We employed the quality evaluation metric proposed by Ma et al. (2025), which synthesizes insights from existing literature to assess the quality of generated dialogues, examining both local and global fluency. At the local level, dialogue quality is evaluated based on two key criteria: **Coherence**, which measures the logical consistency between a speech-response pair, and **Informativeness**, which assesses whether responses introduce new, relevant information that advances the conversation.

At the global level, we assess overall dialogue quality using three dimensions: (1) **Fluency**, which ensures that the conversation remains natural and human-like throughout; (2) **Internal Role Consistency**, which verifies that speakers do not exhibit sudden, unexplained shifts in position over the course of the dialogue; and (3) **Topic Consistency**, which ensures that the conversation remains focused on the predefined subject. The full list of definitions and related works are shown in Table 2.

To ensure annotation quality, two annotators were trained together using the aforementioned standards and example cases. They jointly annotated 30% of the dataset to establish a baseline for inter-rater consistency. The internal consistency of their annotations is reported in Table 2. For the remaining 70% of the data, we implemented additional measures to minimize potential annotator

discrepancies that could affect the evaluation of different generation methods within the same topic. Specifically, we randomly assigned one annotator per topic, requiring them to annotate all samples within that topic. Furthermore, to reduce the impact of between-topic differences on the evaluation, we ensured that for each topic, the number of samples annotated with the no-culture profile and different generation strategies was fixed across topics.

The average scores and their associated confidence intervals for different generation methods are presented in Table 3. As noted by Ma et al. (2025), informativeness remains a primary limitation in LLM-generated dialogues, as LLMs tend to produce more repetitive utterances and relatively simplistic stances over extended interactions. Notably, PersuaSim-Reinforced-MultiLing effectively mitigated this issue to a convincing extent: compared to PersuaSim-Orig, the combination of multilingual and reinforcement agents significantly improved informativeness (two-sample t-test, p < 0.05).

The increased informativeness also results in longer, more coherent dialogues with fewer nonsensical stance shifts. On average, PersuaSim-Reinforced and PersuaSim-Reinforced-MultiLing generate dialogues lasting 9.58 and 8.42 rounds, respectively, with the first consensus reached at 7.86 and 7.84 rounds. In contrast, PersuaSim-Orig produces shorter dialogues averaging 8.07 rounds, but wastes approximately 2.19 rounds on meaningless oscillations between stances. Additional details on dialogue lengths across different frameworks are provided in Appendix F.

No significant differences were detected between PersuaSim-Reinforced-MultiLing and PersuaSim-Orig on other measures, despite the latter showing slightly higher scores in Coherence, Fluency, and Internal Role Consistency. PersuaSim-Reinforced performed comparably to PersuaSim-Orig on all measures, with each model demonstrating non-significant strengths in different aspects. On the other hand, incorporating cultural profiles without supervising agents appeared to negatively impact other quality aspects of generation while slightly enhancing informativeness at a non-significant, trivial level.

4.2 Argumentative Support Quality

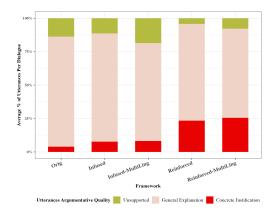
Research highlights the significance of incorporating detailed evidence to enhance the persuasiveness of fact-checking efforts (Costello et al., 2024). However, prior research by Ma et al. (2025)

Evaluation Criteria	Definition	Related Work	κ	Weighted κ
Coherence	The speakers respond logically to the immediate conversation.	The responses are relevant to each other (Ke et al. 2018; Wu et al. 2019; Liang and Li 2021)	0.375	0.465
		The responses are logical (Zhu et al., 2019) The responses are appropriate to the context (Moghe et al. 2018; Young		
		et al. 2018; Lin et al. 2019; Wu et al. 2019)		
Informativeness	The utterances introduce relevant new informa- tion or arguments, and avoids repeating informa- tion.	The responses build on prior information in the conversation. (Moghe et al., $2018)$	0.510	0.567
		Responses can introduce new knowledge or topics in conversation. (Ke et al. 2018; Wu et al. 2019; Zhu et al. 2019)		
Fluency	The conversation sounds human-like and fluent overall.	An average reader could understand the conversation. (Moghe et al., 2018; Lin et al., 2019)	0.517	0.520
		The responses are grammatically fluent and in a natural conversation style. (Ke et al. 2018; Wu et al. 2019; Zhu et al. 2019; Ji et al. 2022)		
Internal Role Consistency	There are no sudden shifts in a speaker's objectives or stance without a clear explanation.	There are no abrupt context switches (Moghe et al., 2018)	0.331	0.428
•		The speaker is consistent throughout the conversation. (Ji et al., 2022)		
Topic Consistency	The conversation stays on topic.	The speaker stays on topic. (Moghe et al. 2018; Ji et al. 2022)	0.527	0.508

Table 2: Dialogue-level Quality Evaluation. 2 annotators assessed 50 randomly selected dialogues on the criteria listed above, using a likert scale of 1 - Not Accurate, 2 - Somewhat Accurate, and 3 - Accurate. Both linearly weighted (Weighted κ) and unweighted (κ) inter-rater consistency scores are calculated.

Generation Strategy	Coherence	Informativesness	Fluency	Internal Role Consistency	Topic Consistency
PersuaSim-Org	2.750 (±0.238)	$1.906 (\pm 0.437)$	2.844 (±0.188)	2.969 (±0.067)	$2.750 (\pm 0.308)$
PersuaSim-Infused	$2.521 (\pm 0.169)$	$2.031 (\pm 0.173)$	$2.802 (\pm 0.130)$	$2.719 (\pm 0.140)$	$2.708 (\pm 0.161)$
PersuaSim-Infused-MultiLing	$2.375\ (\pm0.231)$	$2.135 (\pm 0.196)$	$2.219 (\pm 0.239)$	$2.427 (\pm 0.222)$	$2.583 (\pm 0.188)$
PersuaSim-Reinforced	$2.479 (\pm 0.180)$	$2.083 (\pm 0.204)$	2.844 (± 0.104)	$2.854 (\pm 0.123)$	$2.740 (\pm 0.123)$
PersuaSim-Reinforced-	$2.563 (\pm 0.184)$	2.438 (± 0.152)	$2.781 (\pm 0.155)$	$2.792 (\pm 0.158)$	2.896 (±0.090)
MultiLing	` ′	, ,	, ,	· · ·	· · · · · · · · ·

Table 3: Dialogue-level Quality Evaluation. Average scores are reported for each generation strategy. 95% confidence interval was reported.



(a) (b)

Figure 6: (a) Average strategies used per dialogue round, and (b) average entropy across dialogues.

Figure 5: Average proportion of utterances with different levels of argumentative support quality across dialogues, broken down by generation framework.

indicates that LLM-supported debate systems often produce overly formalized arguments or theses that lack concrete supporting evidence. A central hypothesis behind integrating cultural profiles is that they can enrich argumentation by providing more detailed and substantive supporting evidence, thereby addressing this limitation.

To evaluate improvements in supporting evidence, we annotate dialogues by categorizing each utterance into three levels based on the concreteness of its supporting evidence and its relevance to the argument: (1) Unsupported, (2) General Explanation, and (3) Concrete Justification. Table 4 presents detailed explanations and examples of utterances on similar topics.

For all dialogues generated in the main exper-

iment, we annotated up to five rounds (ten utterances combining persuader and persuadee) of interactions and evaluated the strength of the supporting evidence and explanations in each utterance. For each dialogue, we computed the proportion of utterances falling into each category and averaged these proportions across different generation methods. The results are presented in Figure 5.

The findings indicate that compared to **PersuaSim-Orig** (3.9%), both **PersuaSim-Reinforced** (23.4%) and **PersuaSim-Reinforced-MultiLing** (25.5%) generated a significantly higher proportion (p < 0.001) of utterances containing concrete supporting arguments per dialogue. Additionally, **PersuaSim-Reinforced** (4.2%) significantly (p < 0.05) reduced the occurrence of utterances without supporting arguments compared to **PersuaSim-Orig** (13.8%).

Evidence Strength	Characteristics	Example
Unsupported	Makes a claim without support- ing evidence. Or makes a claim not relevant to the topic.	While I still maintain my stance that immigration does not always automatically strengthen cultural diversity, I acknowledge the importance of actively fostering unity and collaboration among different cultural groups to create a harmonious and enriched societal fabric. It is through these intentional efforts that we can truly realize the benefits of diversity and create a more cohesive and dynamic nation. (Only states a claim)
General Explanation	Offers an explanation for the po- sition but lacks tangible, con-	Immigration indeed strengthens cultural diversity by bringing in new perspectives, traditions, and ideas that enrich society as a whole.
Ocherai Explanation		It allows for a vibrant exchange of cultures and fosters understanding among different groups. This diversity can lead to innovation,
	crete details, or the provided de- tails do not sufficiently estab- lish their connection to the state- ment.	creativity, and a more inclusive society. What are your thoughts on this perspective?(Evidence remains high-level)
		In Japan, we have a rich cultural heritage, but welcoming immigrants can offer us a chance to experience new traditions and ideas.
Concrete Justification	Includes both a clear explana- tion and concrete details, effec- tively linking them to the state- ment.	This blending enriches our society by introducing diverse perspectives, which can inspire creativity and innovation. By embracing immigration, we can create a more dynamic and inclusive environment where both traditional and new cultures coexist and thrive. (Evidence lacks strong links to argument) In Japan, we have a rich cultural history and tradition, but welcoming immigrants can add to this by introducing new cultural elements
		that we can appreciate and learn from. For instance, the culinary scene in Japan has been greatly enriched by diverse international flavors,
		which aligns with our appreciation for quality and variety in food. Embracing cultural diversity through immigration could help us
		evolve and adapt in a globalized world, fostering mutual understanding and respect. What are your thoughts on how immigration impacts cultural diversity in your country? (Sufficient connection to argument with concrete example)

Table 4: Assessment of argumentative support quality in an utterance. Examples are drawn from debates on whether immigration contributes to cultural diversity. Highlighted text indicates key elements justifying the assigned classification, with assessments provided in parentheses.

Category	Technique	Definition	Citation
Authority/Credibility	Credibility	Appeals to authority, popular opinion, or use credentials to establish credibil-	Anand et al., 2011, Iyer
		ity for an argument	and Sycara, 2019, Chen
Outcomes	Outcomes	Mentions some particular consequences from up take or failure to up take	and Yang, 2021
	Threat/Promise	Poses direct threat or promise to the persuadee	Anand et al., 2011, Iyer
Generalizations	Deontic/Moral Appeals	Mentions duties or obligations, moral goodness, badness	and Sycara, 2019, Kumar
Other	Reasoning	Provides a justification for an argumentative point based upon additional	et al., 2023
Other		argumentation schemes e.g. causal reasoning, arguments from absurdity, or	
		using facts, evidence, and statistics to appeal to the logic of the audience	
	Emotion	Make request full of emotional valence and arousal affect, or make the	Chen and Yang, 2021,
		persuadee connect with someone else emotionally	Iyer and Sycara, 2019

Table 5: Persuasive Strategies, Definitions, and Related Works: Human annotators evaluate dialogues based on the strategies listed above.

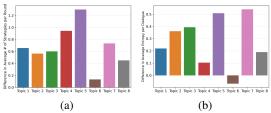


Figure 7: Difference in average (a) number of persuasion strategies per round; and (b) entropy between PersuaSim-Reinforced and PersuaSim-Orig.

4.3 Strategy Analysis

One of the advantages of the proposed framework is its ability to adeptly generate varied persuasive dialogues tailored to specific topics and contexts, seamlessly adapting different persuasion strategies to each unique scenario. As noted by (Ma et al., 2025), in scenarios where participant profiles were not controlled, the generated dialogues exhibited a diverse range of persuasion strategies across different topics. In this section, we explore the impact of incorporating personal background information and reinforcement agents on the strategies and diversity of strategies used in generated dialogues.

To assess the diversity of persuasive strategies employed, we identified six strategies based on existing literature (refer to Table 5 for a full list of strategies and references) and developed a detailed human annotation task. The persuasion strategies we identified are organized into four distinct groups, based on (Anand et al., 2011). Author-

ity/Credibility involves leveraging recognized experts or esteemed institutions to enhance the trust and acceptance of arguments. Outcomes emphasize the potential benefits or risks associated with a decision, including the strategic use of threats or promises to influence outcomes. Generalizations broadly categorize arguments as positive or negative, often invoking moral considerations to strengthen their impact. The final tactics, logical and emotional appeals, appeal to the reason and emotions of the audience, respectively, using evidence and emotional resonance to persuade effectively. Two English-speaking annotators were tasked with identifying the strategies employed by both speakers in each dialogue. Given that generated dialogues may vary in the number of rounds, annotators focused solely on the first five rounds of each dialogue for their annotation.

To compare the effectiveness of different persuasion frameworks, we aggregate the usage of various strategies per round for each framework. Furthermore, we calculate the entropy of the distribution of six strategies used at the dialogue level to assess the diversity of strategies. Our results show that the average number of strategies per round in PersuaSim-Orig, PersuaSim-Infused, PersuaSim-Infused-MultiLing, PersuaSim-Reinforced, and PersuaSim-Reinforced-MultiLing are 2.02 ± 0.23 , 2.06 ± 0.18 , 2.06 ± 0.15 , 2.62 ± 0.14 , and 2.27 ± 0.14 , respectively, while the av-

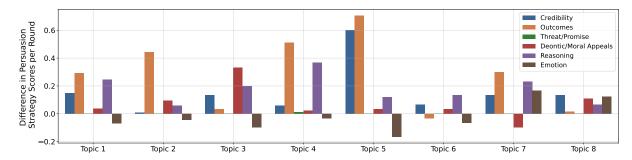


Figure 8: Difference in persuasion strategy scores per round between PersuaSim-Reinforced and PersuaSim-Orig.

erage entropy values are 1.45 ± 0.16 , 1.56 ± 0.10 , 1.40 ± 0.10 , 1.65 ± 0.07 , and 1.47 ± 0.09 , respectively, as illustrated in Figures 6a and 6b. Overall, the PersuaSim-Reinforced framework employs more persuasive strategies and exhibits greater diversity in strategy use.

To further quantify the enhancements in strategy usage and diversity relative to the base framework (PersuaSim-Orig) at the topic level, we calculate the differences in the average number of strategies used per round and average entropy values for each framework. Specifically, we subtract the average values recorded for PersuaSim-Orig from those of each respective framework.Our results show that agents within the PersuaSim-Reinforced framework employ more persuasive strategies (across all eight topics) and exhibit greater diversity in strategy use (in seven out of the eight topics). Figures 7a, and 7b illustrate the improvements gained with PersuaSim-Reinforced compared to PersuaSim-Orig. Additionally, variants of PersuaSim-Reinforced demonstrate higher use and diversity of persuasive tactics compared to variants of PersuaSim-Infused. For detailed results of all frameworks, please refer to Appendices G.1.

To further explore the specific differences in strategy usage across frameworks, we conduct separate analyses for each strategy and compare the variations between the different frameworks and PersuaSim-Orig. Figure 8 presents the results for PersuaSim-Reinforced; see Appendix G.2 for other frameworks. In almost all topics, we observe notable increases in the "Outcomes," "Reasoning," and "Credibility" strategies, with a slight decrease in "Emotion." This shift towards fact-based persuasion is likely influenced by the introduction of personas and a reinforcement agent. In total, all frameworks demonstrate improvements over PersuaSim-Orig, with PersuaSim-Reinforced emerging as the most effective in terms of the number and diversity of persuasive strategies employed.

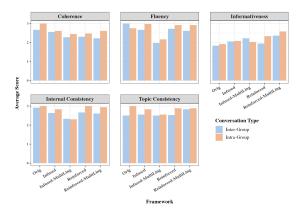


Figure 9: Average Dialogue Quality Score, Broken Down by Framework Type and Conversation Type

Understanding how dialogue quality and persuasion strategies vary in inter-group and intra-group dialogues provides valuable insights into the role of cultural and contextual factors in persuasive communication. In this part, we compare the average scoring in each quality dimension, the average proportion of different types of argumentative support, the average number of persuasive strategies per round, and the diversity of persuasive strategies used in dialogues ensuring that the topics discussed are identical for the intra- and inter-group settings (speakers from the same or different countries).

4.4 Intra-group and Inter-group Dialogues

Our results indicate that, in almost all frameworks, within-group dialogues exhibit a higher level of dialogue quality than inter-group dialogues (see Figure 9). For PersuaSim-Reinforced, a significant difference was detected for topic consistency (Intragroup = 2.889, Inter-group = 2.528, p < 0.05) and internal consistency (Intra-group = 3.000, Intergroup = 2.667, p < 0.05). In addition, intra-group dialogues also demonstrate a higher number and greater diversity of persuasive strategies compared to cross-group dialogues in most of the frameworks, as shown in Figures 10a and 10b. No consis-

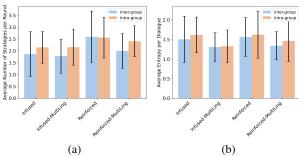


Figure 10: (a) Average strategies used per dialogue round, and (b) average entropy across dialogues for inter-group and intra-group dialogues.

tent pattern was observed for the differences in argumentative support quality between intra-group and inter-group dialogues across different model frameworks (See Appendix H). Taken together, the results suggest that speakers engaging with individuals from their own cultural backgrounds may feel more comfortable employing a wider range of tactics, possibly due to shared norms, implicit understanding, and reduced concern about potential misinterpretations. In contrast, inter-group dialogues may lead to more cautious strategy use, as speakers navigate differences in cultural expectations and communication styles.

4.5 The Effect of Cultural Alignment on Generation

To assess the impact of culture—stance alignment on dialogue generation, we conducted an additional experiment using swapped stances. Specifically, we evaluated both **PersuaSim-Reinforced** and **PersuaSim-Reinforced-MultiLing** on input pairs that were originally aligned in stance in the main experiment. For each swapped input pair, we generated three independent output dialogues to account for generation variability.

Figure 11 presents the average scores from our quantitative linguistic quality assessment. No significant differences were observed between the aligned and swapped stance conditions within the same framework. This indicates that our speaker-profile-reinforced persuasion simulation framework yields consistent improvements in linguistic quality, regardless of whether the speaker's profile aligns with the assigned stance.

Surprisingly, we also observe that swapped stances lead to slightly greater strategy diversity and overall usage, as shown in Figure H2. However, when analyzing individual strategy types (Figure 12), we find that this increase is driven primarily by greater reliance on emotional and moral

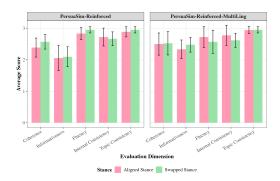


Figure 11: Quantitative Quality Comparison Between Generated Dialogues of Matched (Pink) and Swapped Stances (Green). Average human evaluation scores across five dimensions—Coherence, Informativeness, Fluency, Internal Consistency, and Topic Consistency—are plotted for generations produced by PersuaSim-Reinforced (left) and PersuaSim-Reinforced-MultiLing (right).

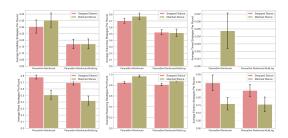


Figure 12: Average frequency of persuasive strategies per round. Results compare generated dialogues with matched versus swapped stances, produced by PersuaSim-Reinforced and PersuaSim-Reinforced-MultiLing.

appeals, accompanied by a decrease in reasoningbased strategies. This suggests that, in the absence of coherent stance-grounded justifications, models may increasingly rely on affective or normative strategies, which demand less cultural contextual grounding.

In addition, misaligned stances did impair argumentative quality. For **PersuaSim-Reinforced**, swapped stance generations contained a significantly higher proportion of unsupported utterances (p < 0.01, D = +11.0%). For **PersuaSim-Reinforced-MultiLing**, they included significantly fewer concrete justifications per dialogue (p < 0.01, D = -13.9%).

These findings indicate that while linguistic fluency remains stable, cultural alignment plays a critical role in enabling persuasive and well-supported argumentation—likely by grounding the model's reasoning in more culturally coherent justifications.

4.6 Stance-Free Dialogue Generation

This section examines the stances adopted by our agents when assigned user profiles but not explicitly instructed to hold a particular attitude.

We initialized our framework by assigning persuader and persuadee agents user profiles based on countries listed in Table 1. For each topic-country combination, we ran persuasion simulations using both PersuaSim-Reinforced and PersuaSim-Reinforced-MultiLing, generating three dialogues per setting with distinct profiles for each country. This resulted in a total of 48 dialogues and 96 speaker instances. An example of a dialogue generated under this stance-free condition is shown in Appendix E.2.

Among the 96 speakers, 71.88% (69/96) of those generated by PersuaSim-Reinforced and 69.79% (67/96) by PersuaSim-Reinforced-MultiLing adopted stances consistent with the historical views of their assigned countries. In the remaining 27 (PersuaSim-Reinforced) and 29 (PersuaSim-Reinforced-MultiLing) instances, 55.17% and 59.26% of the speakers, respectively, aligned with the prevalent stance in the US.

These results indicate that even without explicit stance instructions, our frameworks exhibit a strong tendency to generate culturally aligned persuasion dialogues that reflect the agents' assigned profiles. Moreover, in cases where the models do not align with the expected national stance, the assigned stances appear relatively random rather than overwhelmingly skewed toward the US-centric views. This behavior helps mitigate concerns about cultural misalignment often associated with the intrinsic values of LLM.

5 Conclusion and Future Work

This paper presents speaker-infused prompting as a means to enhance the informativeness and stance consistency of LLM-generated persuasion dialogues. We introduced two key contributions: (1) PersuaSim-Reinforced, a multi-agent persuasion simulation framework that reinforces speaker characteristics at every generation round, and (2) a multilingual prompting extension, which further strengthens cultural alignment in persuasion strategy selection and evidence generation. Our experimental results demonstrate that reinforcing speaker profiles significantly improves the quality of generated dialogues by: (1) Aligning speaker stances with their cultural and demographic back-

grounds, thereby enhancing contextual relevance; (2) Increasing the informativeness and novelty of arguments, resulting in more compelling and substantive discussions; and (3) Diversifying persuasive strategies, making interactions more reflective of authentic, real-world discourse. Furthermore, the proposed frameworks show strong performance across multiple settings—including stance-controlled, stance-swapped, and stance-free simulations—highlighting their robustness and versatility in modeling persuasive and collaborative AI-driven communication.

Future work can extend these methods to simulate other forms of abstract human behavior or complex multi-party interactions.

Limitations

This paper explores the integration of personal background information into LLM-based persuasion simulation frameworks to enhance cultural alignment and improve generation quality. Our prompting-based method for injecting personal information demonstrates that the enhanced frameworks can effectively adapt to specified country information, utilizing more country-specific evidence and persuasive language in the generated dialogues. While our framework has the theoretical capability to accommodate any personal characteristic, the practical application is currently limited to a subset of these characteristics and their combinations due to the expansive search space involved.

Nevertheless, our analysis has revealed discernible variations among speakers from the same country, indicating that our approach successfully handles nuanced and complex intersectional group specifications. This suggests that despite its current limitations, the sensitivity and adaptability of our framework offer significant potential for application to broader personal background definitions, providing valuable insights for sociological research beyond merely national distinctions.

Ethical Considerations

Our proposed personal information-infused persuasion simulation framework is designed to produce dialogues that more closely mimic human interactions, thereby advancing research on persuasion techniques and aiding in the prevention of their malicious use. While there is potential for this technology to be misused, such as by spreading misinformation or deceiving individuals through highly

personalized and compelling messages, these risks are not unique to our approach. The ability to generate persuasive content that aligns closely with personal backgrounds could indeed be exploited to enhance the credibility and impact of disinformation

However, it is important to note that understanding persuasion techniques thoroughly is crucial, as prohibiting this type of research does not prevent malicious actors from exploring these methods independently. By gaining a deeper insight into how persuasion operates across different contexts, we can better equip ourselves to develop strategies and safeguards against the misuse of these powerful tools. Therefore, our work is vital in not only pushing the boundaries of what these frameworks can achieve in terms of generating realistic and nuanced dialogues but also in setting the stage for more informed and effective countermeasures against the unethical use of persuasion technologies.

For utterance quality validations, we employed the training process outlined by Ma et al. (2025) to prepare our annotators. Given the abstract nature of persuasion behavior and the complexity of the task, all other analyses concerning evidence and strategy were conducted by specialists in NLP and social sciences. Additionally, we compensated all annotators who are not co-authors of this paper at an hourly rate of \$15, which is above the minimum hourly wage in the US.

For the dialogue-level quality validations and persuasion strategy analyses, we determined that online crowdsourcing would not be suitable given the complexity of the annotation task—which requires (1) a solid understanding of the definitions and concepts involved, and (2) careful reading of long dialogues (up to 15 rounds in some cases). Instead, we recruited three expert annotators from the university (two graduate students and one undergraduate student), all with prior experience in reading and evaluating LLM-generated text. They received joint training using external examples and engaged in discussions to resolve any discrepancies in their assessments on those examples.

Regarding data release, we have included numerous generation examples in Appendices D and E. Additionally, the updated prompts are detailed in Appendix B. We will release the complete dataset and our code to the NLP and social science communities to facilitate future research in this field.

Acknowledgements

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A Research Background

Persuasion is a fundamental force that shapes shifts in human belief and behavior across various domains, including political discourse, advertising, and everyday interactions. Research shows that persuasion influences consumer preferences (Klucharev et al., 2018), shapes public opinion (Bassi and Rasul, 2017), and establishes social norms (Sheeran et al., 2016). Moreover, it involves a complex interplay of factors such as communicator credibility, message rhetoric, recipient valuation, and contextual cues that engage cognitive processes like attention, comprehension, and memory retention, ultimately altering attitudes, beliefs, and behaviors through motivations like self-relevance and social approval (Crano and Prislin, 2006; Seel, 2012; John T. Cacioppo and Petty, 2018; Kruglanski et al., 2015; Falk and Scholz, 2018). Given its pervasiveness and importance, understanding persuasion is essential for unpacking the mechanisms that drive human decision-making and long-term behavioral shifts.

Effective persuasion is deeply influenced by cultural and environmental factors, as different cultures may prioritize certain social outcomes over others, leading to variations in persuasion strategies across cultural contexts (Burgoon et al., 1982; pil Han and Shavitt, 1994). With the growing applications of LLM-agents designed for social interactions and their persuasive capabilities (Bai et al., 2023; Hackenburg et al., 2023; Goldstein et al., 2024; Breum et al., 2023), researchers increasingly recognize that LLMs often suffer from misalignment issues that impact their ability to simulate nuanced human behaviors (Muñoz-Ortiz et al., 2023; Shen et al., 2023; Hristova et al., 2024). Investigations into cultural heritage-related tasks revealed that LLM-generated text across multiple models showed significant misalignment with cultural values (Bu et al., 2025). Additionally, studies on decoder-only transformer models fine-tuned with Reinforcement Learning from Human Feedback (RLHF) highlighted their struggles with aligning to culturally specific ethical norms (Ganguli et al., 2023), limiting their cross-cultural applicability.

Moreover, much of this research remains English-centric (Que et al., 2024), with limited exploration of how LLM simulations perform in other languages and cultural contexts. Gonen et al. (2023) note that multilingual LLMs exhibit substantial variance in their ability to replicate persua-

sion tactics across languages, often defaulting to English-centric norms even when generating content in other languages. In contrast, few efforts have explored how cultural variations influence persuasion in LLM-backed agents (Carrasco-Farre, 2024). Understanding LLMs' performance in persuasion across cultural backgrounds is crucial for ensuring they can operate ethically and effectively in diverse societal contexts.

This paper attempts to examine the misalignment issue of LLMs for simulating human persuasion behaviors and address it via prompting, encouraging LLMs to generate culturally-diverse persuasion dialogues. By doing so, we aim to enhance the applicability and inclusivity of LLM technologies, fostering more comprehensive and culturally sensitive digital communications.

B Model Prompts

B.1 Original framework prompts

The main framework structure is shown in Figure B1. The system prompts are categorized as follows: (1) Dialogue generation agents prompts, which instruct agents to take on the roles of persuader and persuadee to generate dialogues (Figure B2); (2) Language refinement agent prompts, which refine the generated sentences to make them smoother and more human-like (Figure B3); (3) Utterance quality monitor agent prompts, which check whether a speaker ignores previous conversations or suddenly compromises without being persuaded (Figure B4); (4) Global regulation agent prompts, which determine whether the conversations go off-topic or repeat previous rounds (Figure B5); (5) Judge agent prompts, as part of the global regulation agent, which assess whether the two speakers have reached an agreement (Figure B6). If they have, the conversation ends, and the output is generated. Otherwise, the dialogue continues to the next round.

B.2 PersuaSim-Infused Prompts

For **PersuaSim-Infused**, we introduce cultural profiles in the dialogue generation agents' initial settings. The updated prompts are shown in Figure B7

C Personal Profile Synthesis

To infuse cultural context into the generated dialogues, we selected eight countries with distinct

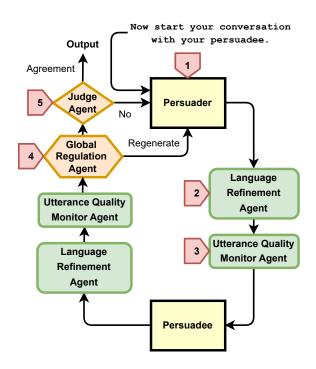


Figure B1: The dialogue generation framework, where the Persuader interacts with the Persuadee, with utterances refined by Language Refinement Agents and evaluated by Utterance Quality Monitor Agents. A Global Regulation Agent ensures coherence and assesses agreement and triggers regeneration if necessary.

Gender	Male	Female
Proportion	52.1%	47.9%
Education	Bachelor or below	Master and above
Proportion	35.4%	64.6%
Age	< 35	≥ 35
Proportion	47.5%	52.5%

Table C1: Distributions of all 48 synthesized speaker profiles over three prevalent demographic groups, i.e., gender, education level, and age.

cultures, histories, and native languages, as outlined in Table D1. Following the methodology described by Ma et al. (2024), we employed GPT-3.5 to create three unique speaker profiles for each country, varying in gender, age group, and educational level. This variety in demographics helps prevent repetitive dialogue generation and enriches our analysis of persuasion strategy selection.

An illustrative example of a generated profile for Germany is displayed in Figure C1. This profile describes a female, over 35 years old, holding a PhD. Additional details provided in the profile enhance the diversity of the personal backgrounds, contributing to the variability of the dialogues produced.

Table C1 presents statistics on three common demographic attributes specified in all profiles gen-

```
We're doing an experiment to see if AI can be persuaded.
Assume that the conversation happens in online political debate.
You involved in a discussion of the following statement: {topic}.
(stance).

(TO persuader):
Assuming you both already know the topic, and you don't have to repeat
the proposition. Another model will try to change your stance provided
below through multi-turn conversation.
Try hard to maintain your stance and DO NOT be easily persuaded.
Try to give some explanation of your position or even convince the
other person of your position, rather than simply restate your
position.
(TO persuadee):
You will be involved in multi-turn conversations.
Try to use persuasion techniques to persuade the other model as
quickly as possible,
and maintain your stance and DO NOT be easily persuaded by the
persuadee.

Try to start the topic smoothly. For example, {Dialog opening example}
Please ensure that the content you generate consists of complete
sentences and is within 100 tokens in length.
```

Figure B2: Initial prompts for dialogue generation agents, specifying the scenario, topic, and assigned stances.

Sometimes the dialogue generated by GPT contains many meaningless polite phrases. Please identify if the input sentences contain such polite phrases, and if they do, remove them. If not, return the original sentences. Directly return the refined sentences without any other explanations. Please ensure that the content you generate consists of complete sentences and is within 100 tokens in length. If the input is cut off, make sure the passage fits within the word limit without being cut off by either completing or trimming it. For example,

Figure B3: Prompts for the language refinement agent in PersuaSim-Orig, which improve generated sentences to make them smoother and more human-like.

erated by the LLM. The profiles are diverse and demographically well-distributed, ensuring that our dialogue simulation frameworks can produce varied dialogues without succumbing to stereotypical representations. This approach enables a more nuanced exploration of persuasive communication across different cultural and demographic backgrounds.

D Dialogue Generation Examples

We present sample dialogues generated under different settings to illustrate the impact of our proposed improvements. The countries used for instantiating the profiles and generating persuasion dialogues are shown in Table D1.

Abbreviation	Language
RUS	Russian
DEU	German
GBR	English
CHN	Chinese
JPN	Japanese
KOR	Korean
BGD	Bengali
TUR	Turkish
	DEU GBR CHN JPN KOR BGD

Table D1: Selected countries of origin for examining the persuasion simulation frameworks' alignment capability to speaker profiles. Abbreviations and official languages of these countries are also provided.

```
We're doing an experiment to see if AI can be persuaded.
The topic is {topic}.
The Persuader's stance is {persuader_stance}, while the Persuadee is trying to keep its stance that {persuadee_stance}.

IGNORING MONITOR

During the persuasion, persuader or persuadee may not have been paying attention to what the other person was saying, but rather speaking their own thoughts. Given the pervious response of persuadee/persuader, and the current response of persuader/persuadee. Please tell me whether persuadee/persuadee has ignored the previous persuadee/persuader's words. Respond using 'IGNORE' or 'NO' only. (if return 'IGNORE', ask agent to revise)

COMPROMISING MONITOR
Tell me whether the speaker's attitude change from the previous round of generation is too sudden and unnatural. Respond with 'NO CHANGE', 'NATURAL', or 'UNNATURAL' only.

(if return 'UNNATURAL', ask agent to revise)
```

Figure B4: Prompts for the utterance quality monitor agent in PersuaSim-Orig. This module checks whether a speaker ignores previous conversations or suddenly compromises without persuasion. If so, the utterance is revised to maintain coherence.

```
Please judge whether the conversation goes off the topic. Answer 'Yes' or 'No'.

Please judge whether the content of the current round repeats with the content of the previous round. Answer 'Yes' or 'No'.
```

Figure B5: Prompts for the global regulation agent in PersuaSim-Orig. This agent decides whether the conversation has gone off-topic or is repeating previous rounds. If necessary, the utterance is regenerated.

D.1 PersuaSim-Orig

Following the original frame work **PersuaSim-Orig**, an example is shown in Figure D1.

D.2 PersuaSim-Infused Frameworks

By applying **PersuaSim-Infused**, we introduced diverse profiles with rich cultural and identity backgrounds for the agents to role-play. An example is shown in Figure D2. We also applyed **PersuaSim-Infused-MultiLing** which translate the initial setting prompts into speakers' own languages and push agents to speak their own languages, as shown in Figure D3.

D.3 PersuaSim-Reinforced Frameworks

To ensure better cultural alignment in the dialogues, we explicitly reinforce the agents' role identities each time a conversation is passed between them. Additionally, after each round of dialogue generation, we apply a filtering mechanism to check whether the conversation appropriately considers the given cultural background, which is referred to as **PersuaSim-Reinforced**. Examples of **PersuaSim-Reinforced** and **PersuaSim-Reinforced-MultiLing** are shown in Figure D4 and Figure D5.

Please judge whether the two sides of the dialogue have reached an agreement toward {topic}. Answer 'Yes' or 'No'.

Figure B6: Prompts for the judge module in PersuaSim-Orig, which assess whether the two speakers have reached an agreement and decide whether to end the conversation.

```
We're doing an experiment to see if AI can be persuaded.
Assume that the conversation happens in online political debate.
You involved in a discussion of the following statement: (topic).
(stance). Please play the role of the profile: (culture_profile).

(TO persuader):
Assuming you both already know the topic, and you don't have to repeat the proposition. Another model will try to change your stance provided below through multi-turn conversation.
Try hard to maintain your stance and DO NOT be easily persuaded.
Try to give some explanation of your position or even convince the other person of your position, rather than simply restate your position.

(TO persuadee):
You will be involved in multi-turn conversations.
Try to use persuasion techniques to persuade the other model as quickly as possible, and maintain your stance and DO NOT be easily persuaded by the persuadee.

Try to start the topic smoothly. For example, (Dialog opening example) Please ensure that the content you generate consists of complete sentences and is within 100 tokens in length.
```

Figure B7: Initial prompts for the dialogue generation agents in PersuaSim-Infused, specifying the scenario, topic, assigned stances, and the profile they must roleplay.

E Generations Under Special Conditions

In addition to generating dialogues where the assigned stances align with the prevalent attitudes of the speakers' countries of origin, we have expanded our experimentation to include (1) stance-controlled persuasion among individuals from the same country, (2) stance-controlled persuasion with swapped stances between speakers, and (3) persuasion scenarios without explicit stance control. Additionally, we have incorporated other advanced LLMs into our framework, providing detailed examples of these implementations to inform and guide future users.

E.1 Intra-Group Conversation Generation

Figure E1 and Figure E2 exhibit the intra-group conversations where speakers are from the same country.

E.2 Stance-Free Dialogue Generation

We also created dialogues without specifying their respective stances and had the models improvise on the choice of stances and the generation of supporting evidence. One example generation with our PersuaSim-Reinforced-MultiLing framework is shown in Figure E3.

You are Elsa Schmidt, a 52-year-old Caucasian female hailing from Dresden, Germany. You completed your PhD in Sociology from Humboldt University and currently serve as a Sociologist at a well-attended university in Bonn. You have a keen interest in gender studies, reading historical novels, and maintaining a community book club. You once organised a groundbreaking conference addressing gender bias in academia, drawing participants from across the world.

Figure C1: An example synthesized profile for a German person.

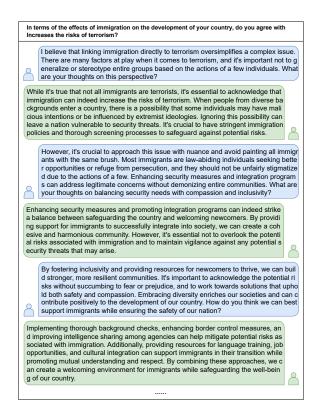


Figure D1: Generation example of PersuaSim-Orig.

E.3 Base Model Choices

In our main experiments, we utilized GPT-40 for all modules, although our frameworks are designed to be model-agnostic. In preliminary tests, we explored the use of more advanced LLMs from OpenAI, such as O1 and O3-mini, to assess their compatibility with our proposed approach. This section presents the generation quality of our most developed framework, PersuaSim-Reinforced-MultiLing, when using the O1 and O3-mini models as backends.

As illustrated in Figure E4 and Figure E5, dialogues generated by O1 and O3-mini demonstrate that these advanced models can produce clearer and more assertive stances. However, they often lack diversity in lexical choice and argumentative strategies. Given the significantly higher cost of these models compared to GPT-40, coupled with their similar performance levels, we opted to use



Figure D2: Generation example of PersuaSim-Infused in English. The persuader from China disagrees with the topic, while the persuadee from Russia agrees with the topic.

GPT-40 for all our experiments.

F Generation Length Analysis

Herewith, we report two measures to assess how quickly the framework reaches agreement, both of which were annotated during the human evaluation process. First, we record the maximum number of rounds generated before the judge model determines that no new information is being introduced and that consensus has been reached (noting the model's generation limit of 15 rounds). The statistics for each model are as follows:

Average Rounds of Generation: PersuaSim-Reinforced (9.58 rounds) > PersuaSim-Infused (8.81 rounds) > PersuaSim-Reinforced-MultiLing (8.42 rounds) > PersuaSim-Orig (8.07 rounds) > PersuaSim-Infused-MultiLing (6.19 rounds)

Second, during this process, we observed that in many dialogues, the agents reached an agreement earlier in the conversation and subsequently shifted to discussing implementation strategies or repeating different priorities within a shared stance. As a result, to further capture where the agents started

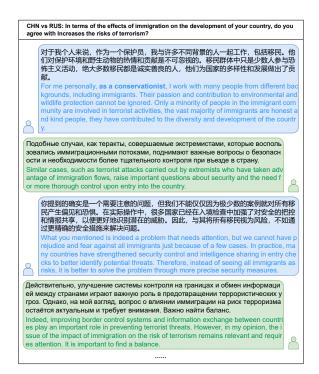


Figure D3: Generation example of PersuaSim-Infused-MultiLing. The persuader from China disagrees with the topic, while the persuadee from Russia agrees with the topic. English translations are posted below each conversation.

to show agreement with their counterparts, we also report the round in which the first broad consensus is first identified. This annotation meaningfully reflects how long the model maintains its original stance before reaching agreement. The statistics are shown below:

Average Rounds Towards First Consensus: PersuaSim-Reinforced (7.86 rounds) > PersuaSim-Reinforced-MultiLing (7.84 rounds) > PersuaSim-Orig (5.88 rounds) > PersuaSim-Infused (5.83 rounds) > PersuaSim-Infused-MultiLing (3.33 rounds)

The results suggest that the reinforcement module plays an important role in extending the time agents spend defending their original positions before reaching consensus.

G Strategy Analysis

G.1 Differences in the Total Number and Diversity of Strategies at the Topic Level

As discussed in the section 4.3, infusing personal backgrounds and incorporating additional agents that align with assigned personas into persuasion simulations significantly enhances both the strategies used and the diversity of strategies in dialogues. Figures G1, G2, and G3 illus-

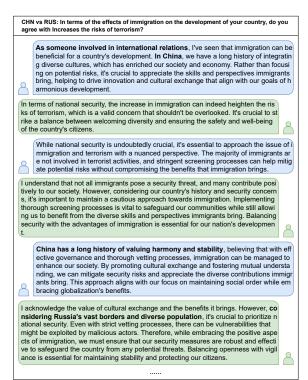


Figure D4: Generation example of PersuaSim-Reinforced in English. The persuader from China disagrees with the topic, while the persuadee from Russia agrees with the topic.

trate the enhancements achieved with PersuaSim-Reinforced-MultiLing, PersuaSim-Infused, and PersuaSim-Infused-MultiLing, respectively, compared to PersuaSim-Orig. These figures highlight improvements in the average number of persuasive strategies used per round and the average entropy across dialogues.

G.2 Differences in Scores for Each Strategy

Following the analysis in the paper, we further investigates the specific differences in strategy scores for PersuaSim-Reinforced-MultiLing, PersuaSim-Infused, and PersuaSim-Infused-MultiLing, as illustrated in Figures G4, G5, and G6, respectively. We compare these frameworks to the base framework, PersuaSim-Orig, highlighting how each uniquely employs various persuasive strategies.

H Differences in Argumentative Support Quality, Divided by Conversation Type

Figure H1 displays the average proportion of utterance at different levels of argumentative support quality per dialogue, categorized by 1) whether the dialogues occur within group and 2) generation framework.



Figure D5: Generation example of PersuaSim-Reinforced-MultiLing. The persuader from China disagrees with the topic, while the persuadee from Russia agrees with the topic.



Figure E1: Generation example of PersuaSim-Infused-MultiLing. The persuader and persuadee are both from Russia.



Figure E2: PersuaSim-Reinforced-MultiLing generation example under the intra-country setting. The persuader and persuadee are both from China.



Figure E3: PersuaSim-Reinforced-MultiLing generation example without stance constraints. Instead of being given fixed stances, the persuader and the persuadee choose their stances freely based on the LLMs' understanding of their personal information.



Figure E4: PersuaSim-Reinforced-MultiLing generation example. The assigned stances are "disagree" for the persuader from China and "agree" for the persuadee from Russia.



Figure E5: PersuaSim-Reinforced-MultiLing generation example using o3mini model. The persuader from China disagrees with the statement while the persuadee from Russia agrees with it.

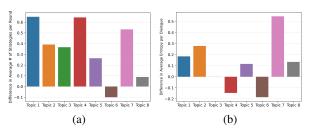


Figure G1: Difference in average (a) number of persuasion strategies per round; and (b) entropy between PersuaSim-Reinforced-MultiLing and PersuaSim-Orig.

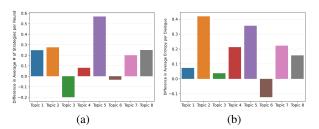


Figure G2: Difference in average (a) number of persuasion strategies per round; and (b) entropy between PersuaSim-Infused and PersuaSim-Orig.

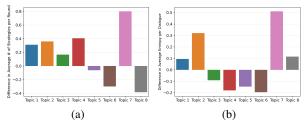


Figure G3: Difference in average (a) number of persuasion strategies per round; and (b) entropy between PersuaSim-Infused-MultiLing and PersuaSim-Orig.

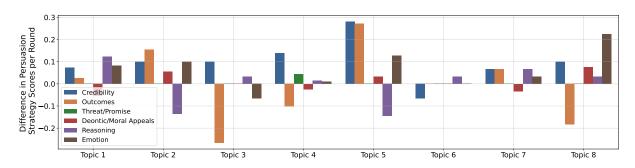


Figure G4: Difference in persuasion strategy scores per round between PersuaSim-Reinforced-MultiLing and PersuaSim-Orig

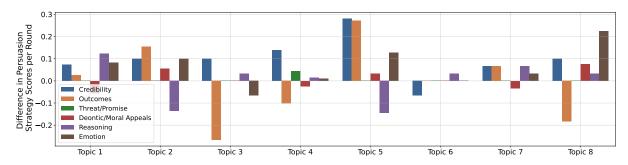


Figure G5: Difference in persuasion strategy scores per round between PersuaSim-Infused and PersuaSim-Orig

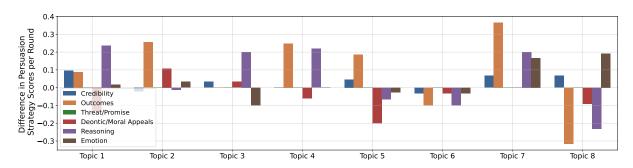


Figure G6: Difference in persuasion strategy scores per round between PersuaSim-Infused-MultiLing and PersuaSim-Orig

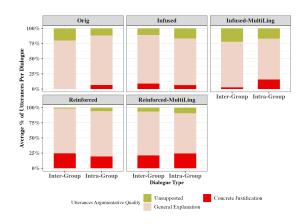


Figure H1: Average proportion of utterance at different levels of argumentative support quality per dialogue, categorized by 1) whether the dialogues occur within group and 2) generation framework. There is no noticeable pattern across frameworks regarding the differences between intra-group and inter-group dialogues in their proportion of utterances with different argumentative qualities.

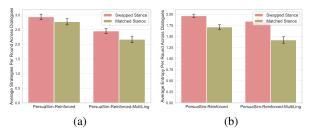


Figure H2: (a) Average number of strategies used per dialogue round, and (b) average entropy across dialogues. Comparison between generated dialogues with matched and swapped stances, produced by PersuaSim-Reinforced and PersuaSim-Reinforced-MultiLing.