Convergence, Reciprocity, and Asymmetry: Communication Accommodation Between Large Language Models and Users Across Cultures

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Abstract

The increasing adoption of conversational agents powered by large language models (LLMs) raises questions about its effects across culturally diverse interactions. While these agents are linguistically versatile and multilingual, their ability to adapt along cultural dimensions–defined as geographically and communally nurtured sets of values and behavioral norms–lacks close scrutiny of both their design and deployment. To achieve inclusive conversational AI, it is essential to understand how agents adapt to users from diverse cultural backgrounds. In this study, we analyze dialogues between human users from different countries and LLM-powered agents to examine how both parties adapt their word use, a salient aspect of linguistic styles, toward one another throughout casual conversations. Our analysis reveals that LLMs exhibit varying degrees of style matching based on users' national cultures and demonstrate asymmetric adaptation when interacting with culturally diverse users. Moreover, we observe a reciprocal dynamic where both the LLMs and users from certain cultures adjust their styles in response to one another. Additionally, our findings support the hypothesis that LLMs and users naturally converge in conversational styles over the course of interactions, mirroring the dynamics of human conversations that accommodate and converge. To develop localized and culturally aware agents, there's a potential to utilize such cross-cultural convergence process during fine-tuning to align LLMs.

Introduction

Conversational agents powered by large language models (LLMs), such as ChatGPT, are reshaping how humans interact with computers, necessitating a comprehensive understanding of these emerging dynamics. Recent work suggests that conversational agents that emulate the communication style of their users can significantly boost user engagement (van Pinxteren, Pluymaekers, Lemmink, & Krispin, 2023). This adaptation process, in which one party adjusts their communication style to more closely resemble that of their interlocutor, is often referred to as style matching.

Style matching is grounded in sociolinguistic observations of how human interlocutors adapt their communication styles (e.g., word choices, tones, utterance compositions), Communication Accommodation Theory (CAT) (Giles, Ogay, et al., 2007) theorizes that, driven by an intrinsic drive for social (dis-)integration and signaling, people adapt their communication styles to (dis-)align with their interlocutors. Drawing on research on style matching in human interactions (Wagner, Punyanunt-Carter, & McCarthy, 2022), conversational agents that adapt variables such as message length, tone, cognitive style, or word choice to mirror users' communication patterns can enhance engagement and foster more positive attitudes (Mortazavi, Taheran, & Amiri, 2024; Riefle et al., 2023). Moreover, cultural norms shape adaptation behaviors; for instance, individuals from collectivist cultures may adapt more in diverse group settings, especially with enhanced visibility of interlocutors (Wang & Fussell, 2010).

Despite this understanding, the dynamics of mutual adaptation and communication style convergence remain underexplored in interactions involving non-human actors, such as LLM-powered conversational agents, especially in cross-cultural contexts. LLMs have yet to fully integrate the semantic, textual, and pragmatic dimensions of communication (Ji, 2024), nor do they posit capability for self-explanation or consistently outperform humans (Trott, Jones, Chang, Michaelov, & Bergen, 2023). These gaps raise questions about whether and how conversational agents and users mutually adapt their communication styles, especially given that cultural backgrounds shape how humans express themselves and engage in conversations. This study addresses this gap by investigating how cultural contexts influence communication dynamics between humans and conversational agents, hypothesizing that style matching behaviors observed in human-to-human interactions will also manifest, with LLMs adapting to diverse cultural contexts.

Leveraging Hofstede's cultural framework (Hofstede, Hofstede, & Minkov, 2005), which describes the cultural dimensions of different societies such as individualism and power distance, this study examines how these dimensions shape communication adaptation. We probe communication accommodation and adaptation through the lens of linguistic features using tools like the Linguistic Inquiry and Word Count (LIWC) (Pennebaker, Francis, & Booth, 2001) and the Language Style Matching (LSM) (Ireland & Pennebaker, 2010). These methods allow us to assess the subtle, yet crucial, dynamic interplay between user and conversational agent. This study addresses three core research questions that will improve our understanding in how people conversationally interact with LLM, as well as the dynamic properties of LLM when situated in interactions with humans:

RQ1: Do national cultures of different placements along Hofstede's cultural dimensions influence linguistic style-matching between users and LLM-powered conversational agents?

RQ2: Does communication accommodation between

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users and conversational agents increase as the conversation is prolonged?

RQ3: Do users adapt their communication styles to the conversational agents and vice versa?

We analyzed 1,500 user-agent conversations, mapping users' birth countries to Hofstede's dimensions and evaluating style matching. Our findings reveal that style matching in linguistic markers related to necessity and obligation is more pronounced in both user and agent responses, particularly in interactions with users from high-hierarchy cultures compared to those from low-hierarchy cultures. Moreover, style matching increases over time, mirroring convergence patterns observed in human-to-human interactions, with further analysis revealing that LLMs excel in aligning with clear linguistic patterns but face challenges in adapting to psychological and contextual nuances. We also observed asymmetry in adaptation, with LLMs adapting more to specific cultural contexts and users reciprocating in some cases.

These results highlight the potential of devising single LLMs to adapt to diverse cultural backgrounds while improving alignment through prolonged interactions. By integrating these insights, this study advances the development of culturally inclusive AI systems and fosters more effective accommodations for the users.

Related Work

Communication Accommodation Between Users and Conversational Agents

Previous research has demonstrated that users tend to prefer agents that adapt to their communication styles (Mortazavi et al., 2024; Riefle et al., 2023). For instance, customer engagement increases when the chatbots exhibit similar characteristics and lifestyle congruency with the user (Loureiro, Ali, & Ali, 2024). Additionally, integrating linguistic alignment—where chatbots mimic users' word choices, sentence structures, and language style—has been shown to decrease user frustration and perceived task workload, thus improving overall interaction quality (Spillner & Wenig, 2021).

Direction of Communication Accommodation

Prior work has found asymmetry in communication adaptation during cross-cultural interactions (Li & Rosson, 2012; Wang, Fussell, & Setlock, 2009; Wang & Fussell, 2010). For instance, studies show native speakers often accommodate non-native speakers in conversation but not vice versa (Li & Rosson, 2012). Similarly, mixed-culture settings see greater adaptation efforts by individuals from collectivist cultures (Wang et al., 2009).

While previous studies have explored aspects of communication accommodation, the specific variations that arise when users from diverse cultural backgrounds interact with conversational agents remain underexplored. Recognizing that such adaptations are typically asymmetrical in cross-cultural interactions, our study aims to fill this gap by analyzing conversations between agents and users from various global contexts. We specifically examine how a user's cultural background and the duration of interaction influence communication adaptations, as well as the directionality of these adaptations between users and conversational agents.

Dataset

We use PRISM and apply Hofstede's cultural dimensions framework for our study.

PRISM (Kirk et al., 2024) is an open-sourced dataset consisting of 8,011 conversations between 1,500 participants from 75 countries and large language models such as GPT-4 and Claude-2. It comprises 27,172 interactions where human messages are met with model responses. The participants disclosed their sociodemographics, such as age, gender, and birth country making this dataset uniquely suitable for the aim of our research.

Hofstede's cultural dimensions (Hofstede et al., 2005) offer a widely applied framework for understanding cultural variations at the level of national cultures essential for our analysis:

- Power Distance Index (PDI) indicates how societies accept hierarchical order without need for justification. Higher scores reflect acceptance of inequality and centralized power, while lower scores favor egalitarianism.

- Individualism versus Collectivism (IDV) shows whether societies emphasize personal (low IDV) or collective achievement and relationships (high IDV).

- Masculinity versus Femininity (MAS) depicts the preference for achievement and rewards for success (higher MAS) versus cooperation and quality of life in society.

- Uncertainty Avoidance Index (UAI) measures the degree to which a society tolerates uncertainty and ambiguity. High UAI indicates conservative, whereas low UAI indicates more inclusive.

- Long Versus Short-Term Orientation (LTOWVS) contrasts societies that plan for the future (higher LTOWVS) with those that focus on short-term outcomes and maintaining traditions.

- Indulgence versus Restraint (IVR) measures the degree of freedom societies permit in fulfilling human desires in having fun (high IVR) versus pessimism.

Table 1: Example LIWC Categories and Sample Words

Category	**Example Words**
Cognitive Processes	but, not, if, or, know
Social Behavior	said, love, say, care
Emotion	good, love, happy, hope

Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2001) is a comprehensive text analysis tool that categorizes over 12,000 words and emoticons into over 100 predefined categories as shown in Table 1. These LIWC categories are further clustered as *category groups* to characterize key dimensions salient in language use, such as Psychological Process, Perception and Linguistic Dimensions. Designed and validated to assess linguistic, cognitive, and emotional properties of text, LIWC quantifies the frequency of words associated with different psychological states and processes. By providing percentage-based breakdowns across pre-constructed and validated categories, LIWC offers insights into emotional states, cognitive styles, and social dynamics reflected in language.

Method

To assess communication accommodation between users and conversational agents across diverse cultural dimensions, we used LIWC to analyze utterances from both parties, quantifying their linguistic, cognitive, and emotional dimensions. We then applied LSM to measure the degree of similarity in word usage within LIWC-defined categories, capturing how conversational agents align their linguistic styles with users. The LSM (Ireland & Pennebaker, 2010) for a specific LIWC linguistic category is computed using the following formula:

$$\mathrm{LSM}_{i,t} = 1 - \frac{|U_{i,t} - C_{i,t}|}{U_{i,t} + C_{i,t} + 0.0001} \tag{1}$$

Here, $\mathrm{LSM}_{i,t}$ represents the LSM score for the $i-th$ LIWC linguistic category derived from the LIWC dictionary for a user at turn t. Specifically, $U_{i,t}$ denotes the proportion of words within the $i-th$ category used by a user at turn t, while $C_{i,t}$ represents the corresponding proportion used by the conversational agent at turn t. The constant 0.0001 in the denominator is included to avoid division by zero when neither party uses words from a given category. A LSM score is a normalized metric ranges from 0 (no similarity) to 1 (perfect alignment).

Impact of Cultural Dimensions on Communication Accommodation

To assess how cultural dimensions influenced style matching between users and conversational agents, we evaluated LSM differences as a function of cultural dimensions using linear mixed model analysis. Using Hofstede's framework, countries were categorized into four quantiles (e.g., Individualism is $IDV = 4$, Collectivism is $IDV = 1$). The model integrates the cultural dimensions to predict LSM for each conversation i by user j as follows:

$$\begin{aligned} \mathrm{LSM}_{i,j} &= \beta_0 + \beta_1 \mathrm{PDI}_{i,j} + \beta_2 \mathrm{IDV}_{i,j} + \beta_3 \mathrm{MAS}_{i,j} \\ &+ \beta_4 \mathrm{UAI}_{i,j} + \beta_5 \mathrm{LTOWVS}_{i,j} + \beta_6 \mathrm{IVR}_{i,j} + \varepsilon_{i,j} \end{aligned} \tag{2}$$

In this model, $\mathrm{LSM}_{i,j}$ denotes an array of 112 LSM scores, each derived from a distinct LIWC category, calculated for each conversation i between user j and the conversational agent. Specifically, $\mathrm{LSM}_{i,j}$ is aggregated over all $\mathrm{T}_{i,j}$ turns in conversation i with user j by $\mathrm{LSM}_{i,j} = \frac{1}{T_{i,j}} \sum_{t=1}^{T_{i,j}} \mathrm{LSM}_{i,t}$. The fixed effect coefficients β_0 through β_6 quantify the average influence of each cultural dimension on these LSM scores. The term $\varepsilon_{i,j}$ captures the random error, representing variability in LSM that is not explained by the cultural dimensions. Given the large number of repeated tests (112 LSM measures), we applied the Bonferroni correction (Dunn, 1961) to adjust the significance level for multiple comparisons, ensuring robustness against Type I errors.

Impact of Conversation Length on Communication Accommodation

To investigate the relationship between communication accommodation and conversation length, we aimed to determine whether LSM increased, decreased, or remained stable as the interaction lengthened, thereby indicating potential convergence or divergence in communication styles over time. We quantitatively analyzed the progression of interactions throughout a conversation by introducing Turn_{ij}, a variable that tracks turn-taking patterns at each stage of the dialogue within equation 2. This allows us to directly measure the impact of prolonged engagement on LSM in our extended model.

To provide stringent evidence and contextualize the findings from the mixed-effects models, we calculated an aggregated LSM by averaging all LSM measures across the dataset and applying the same mixed-effects model. The coefficient of $\mathrm{Turn}_{i,j,t}$ from this aggregated LSM model to serve as a benchmark, which was compared against individual LSM coefficients using a z-test to assess whether conversation length effects on each variable deviated from the average. To account for multiple comparisons, we applied a Bonferroni correction to the p-values obtained from the z-tests. The adjusted p-values were then used to determine the statistical significance of the differences. For significant differences after correction, we examined the magnitude of the effects to understand how communication styles evolved during extended interactions. If an individual coefficient exceeded the aggregated coefficient, this indicated style convergence, reflecting increased alignment in communication over time. Conversely, a smaller individual coefficient suggested style divergence, representing reduced alignment as the conversation progressed.

This approach provided a rigorous evaluation of how conversation length influenced communication accommodation across linguistic dimensions, identifying which aspects tended to converge or diverge during prolonged interactions.

Direction of Communication Accommodation

To understand whether users change their communication styles to adapt to agents or vice versa, we utilized the Granger causality test (Granger, 1969) which is a statistical test on two time series to determine the causal relationship. Specifically, it evaluates whether past values of one time series (e.g., LIWC categories from users) predict future values of another (e.g., LIWC categories from agents), or vice versa. If adding lagged values of one time series significantly improves the prediction of the other, Granger causality is established. For example, if past user behaviors predict agent behaviors, it indicates that agents adapt to users. Conversely, if past agent behaviors predict user behaviors, it suggests users accommodate the agents. Mutual causality occurs when both directions hold true. As Granger causality requires stationarity, we used the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) to verify and transform non-stationary time series before applying the analysis. A lag of 1 was used in the test.

This approach helps elucidate the dynamic interplay between users and conversational agents, revealing how communication accommodation unfolds in digital interactions.

Results

RQ1: Do national cultures of different placements along Hofstede's cultural dimensions influence linguistic style-matching between users and LLM-powered conversational agents?

To assess whether Hofstede's cultural dimensions influence style matching between users and LLM-powered conversational agents, we analyzed the linguistic similarity employed during these interactions. Style matching occurs when one party adjusts their communication to more closely resemble the style of the other party.

Our analysis reveals that the Power Distance Index (PDI) significantly influences communication style matching, particularly in terms of expressions related to necessity and obligation such as "have to", "need", "had to", and "must". Statistical results reveal a notable difference ($\beta_1 = 0.1575$, $p = 0.0003$) in the communication style matching of these terms between high (PDI_4) and low (PDI_1) PDI countries. Specifically, both users and conversational agents have higher similarity in communication styles related to need, necessity, and obligation in conversations with users from high PDI countries (PDI_4) compared to those from countries with lower PDI (PDI_1). This finding suggests that the hierarchical nature of high PDI societies influences communication patterns to a significant extent, reflecting a cultural predisposition towards more formally structured expressions of necessity and obligation. Other cultural dimensions did not exhibit statistically significant effects on style matching, underscoring the particular salience of PDI in shaping these interactional dynamics.

RQ2: Does communication accommodation between users and conversational agents increase as the conversation is prolonged?

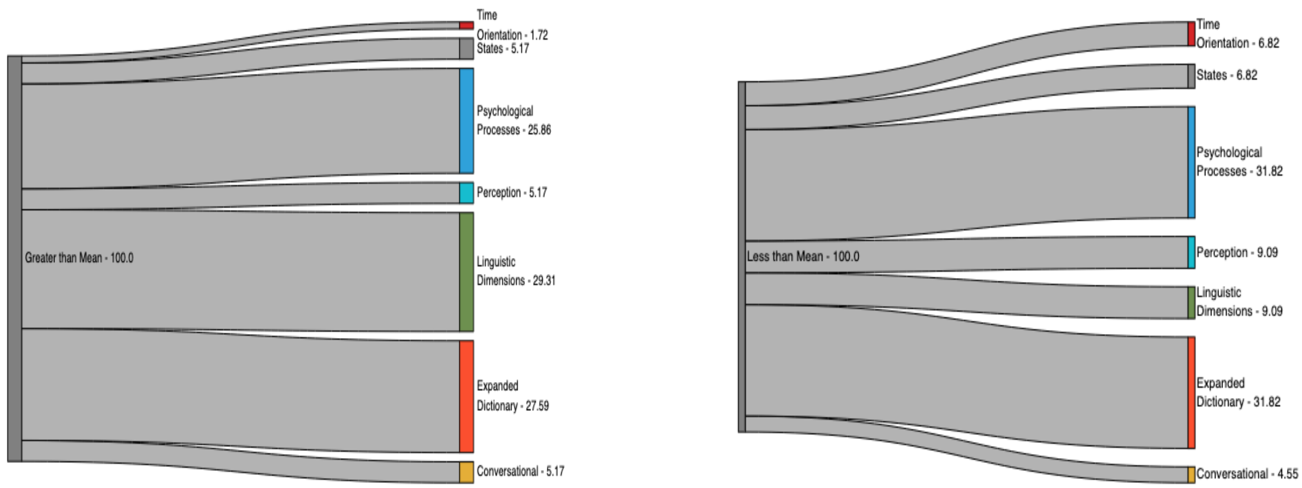
Our analysis of communication accommodation examined whether prolonged interactions between users and conversational agents lead to increased linguistic alignment as indicated by LSM. Using a mixed-effects modeling approach combined with a Bonferroni-corrected z-test, we compared the effect of conversation length (Turn_{ij}) on each LSM category against the overall effect derived from an aggregated LSM model.

Our results support the hypothesis that LLMs and human users tend to converge in conversational styles over the course of interactions, mirroring the dynamics of human conversations that accommodate and adapt to each other's communication styles. Overall, we have 98 LSM with significant adjusted p-value ($p < .00044$). The analysis revealed that in 58 out of 98 significant LSM categories, the effect of conversation length was greater than the overall mean effect, indicating a more pronounced increase in LSM as conversations lengthen. In other words, nearly 59% of the significant LSM categories demonstrated convergence, suggesting that as conversations progress, the utterances between human users and LLMs become increasingly similar, surpassing the expected baseline of linguistic similarity. This finding highlights the ability of LLMs to adapt dynamically to users' communication styles over time, further reinforcing their potential to emulate human-like conversational patterns. In contrast, 41% of the LSM categories (40 out of 98) exhibited divergence, where the effect of conversation length was weaker than the overall mean effect as the conversation progressed.

To further understand which LIWC *category groups* tend to converge or diverge more throughout the conversational process, we calculated the percentage differences in the presence of different *category groups* among the overall converging versus diverging categories (Figure 1). The results revealed that the *category group* of Linguistic Dimensions (+20.22%) exhibited the greatest positive percentage difference in favor of convergence. Specifically, 29.31% of the 58 converging LIWC categories are classified under Linguistic Dimensions, whereas only 9.09% of the 40 diverging LIWC categories fall into this category. The positive differences suggest that conversations are more likely to align in linguistic aspects such as function words, pronouns, determiners, auxiliary verbs, and other grammatical categories, reflecting the LLM's strong capability in adapting to linguistic patterns during dialogue. This trend is likely influenced by the LLM's extensive exposure to written texts in its training data, which emphasizes linguistic consistency and formal language structures over spontaneous conversational variations. In contrast, *category groups* including Psychological Processes (-5.96%) and Time Orientation (-5.10%) demonstrated negative differences, indicating that LLMs tend to struggle with the psychological and temporal aspects of language alignment, resulting in a greater tendency toward diverging from the users. This could be due to the dynamic and context-dependent nature of psychological and temporal language, which is harder to capture through static, text-based training data.

RQ3: Do users adapt their communication styles to the conversational agents and vice versa?

Building on our analyses of how cultural dimensions influence communication styles and the progressive alignment of these styles throughout interactions, we now focus on the directionality of communication adaptations between users and conversational agents, investigating through Granger causality tests whether adaptations are more pronounced from users



(a) Proportion of *category groups* among LIWC categories that converge

(b) Proportion of *category groups* among LIWC categories that diverge

Figure 1: Relative presence of LIWC *category groups* showing convergence versus divergence in prolonged conversations.

towards the models or vice versa. We are particularly interested in how these adaptations differ between users from cultures with high versus low quantization (i.e., PDI $= 4$ versus PDI $= 1$) on Hofstede's cultural dimensions, providing insights into the dynamic interplay of culture in communication behaviors.

To quantitatively ascertain the direction and magnitude of these adaptations, we apply Granger causality analyses across over 100 LIWC categories, assessing the adaption influence from both users to agents and from agents to users. We categorize and quantify the significance ($p < 0.05$) of these adaption relationships for each cultural dimension, detailing both the direction of adaptation and the relative impact. Specifically, we compute the proportion of categories showing significant Granger causality, summarizing our findings in terms of which cultural dimensions exhibit the strongest influence on communication accommodation and its directionality. The findings predominantly suggest that models are more frequently adapting to users rather than the converse. However, it should be acknowledged that there is a discernible level of user adaptation towards models, as evidenced in Figure 2. To further understand the differences in adaptation behaviors, we conduct Chi-square tests to determine whether each adaptation direction—Model Adapts to Users and Users Adapt to Model—demonstrates significant differences between cultures with high versus low quantization levels.

Our analysis indicates that models demonstrate a greater tendency to adapt to users from cultures with higher levels of individualism (IDV_4=72%) compared to those from collectivist cultures (IDV_1=64%), with these differences being statistically significant ($p = 0.0144$). Conversely, the manner in which users adapt to models across individualistic and collectivistic cultures does not show significant variation ($p =$ 0.3151), suggesting that the influence of individualism versus collectivism on user behavior towards models may be more nuanced or driven by other factors.

Users from cultures with lower power distance are more likely to adapt to the model (PDI_1=31%) than the users from more hierarchical cultures (PDI_4=25%), the difference is statistically significant ($p = 0.0358$). On the other hand, the differences in how models adapt to users do not differ significantly between different PDI levels ($p = 0.2100$).

In some cases, we observe a reciprocal relationship where the models adapt to the users more while the users also show higher adaptation. For instance, models adapt to users substantially more ($p < .0000$) in optimistic cultures (IVR_4=81%) compared to pessimistic cultures (IVR_1=52%). At the same time, IVR_4 users also showed up to 46% adaptation to models compared to 19% from IVR_1 users ($p <$ .0000). Similar reciprocal phenomena ($p < .0000$) were also observed in short-term oriented cultures ($LTOWVS_1$), masculine cultures (MAS_4), and inclusive cultures (UAI_1).

These results underline the complex interplay between cultural dimensions and communication adaptation behaviors, occurring both from models to users and vice versa. The significant effects observed indicate that conversational agents can dynamically adjust their interactions in response to users' cultural backgrounds, as reflected in language use patterns. This finding further underscores the potential of leveraging natural language convergence processes as a foundation for developing culturally adaptive AI systems that more effectively align with human communicative behaviors and cultural nuances.

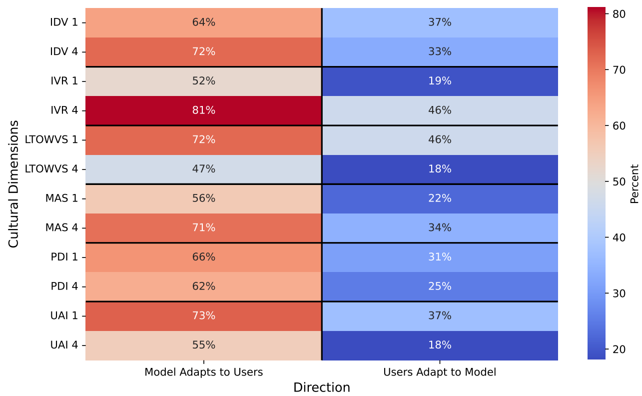


Figure 2: Heatmap of Communication Adaptation Across Hofstede's Cultural Dimensions. This heatmap quantifies the percentage of significant Granger causality findings for Individualism versus Collectivism (IDV), Indulgence versus Restraint (IVR), Long-Term versus Short-Term Orientation (LTOWVS), Masculinity versus Femininity (MAS), Power Distance Index (PDI), and Uncertainty Avoidance Index (UAI), highlighting a greater propensity for models to adapt to users than vice versa, thus demonstrating the conversational agents' adaptivity to users across cultural dimensions.

Discussion

This paper, using Hofstede's framework, explored how cultural dimensions influence communication accommodation between users and conversational agents.

Our analyses revealed that cultural dimensions, particularly those related to social hierarchy, significantly impact style matching of users and conversational agents. Specifically, LLM interactions involving users from high hierarchical cultures (i.e., countries with high PDI scores) exhibit higher style matching in command and necessity-driven communication.

Moreover, the analysis of prolonged interactions revealed that, in general, Language Style Matching increases as conversations progress, suggesting a convergence in communication styles over time. This finding supports the hypothesis that interactions between humans and chatbots exhibit similar patterns of style matching as seen in human-to-human communication. Further analysis highlighted the strengths of LLMs in aligning with users' linguistic patterns (e.g., use of functional words and pronouns) while underscoring their limitations in adapting to the psychological and contextual subtleties required for fuller communication accommodation.

To further understand the directionality of communication adaptations, we investigated whether users change their communication to adapt to the conversational agents or vice versa. Our analysis predominantly suggests an asymmetric relationship where the models adapt more frequently to users rather than the reverse. Moreover, models adapt significantly more to users from cultures with higher individualism compared to collectivist cultures. Conversely, user adaptation to models does not significantly vary between individualistic and collectivist cultures. Additionally, users from cultures with lower power distance are more likely to adapt to the model compared to users from more hierarchical cultures. However, model adaptation to users does not significantly differ between different PDI levels.

Interestingly, in some cultural contexts, we observed a reciprocal relationship where both models and users showed higher levels of adaptation. For example, models adapted significantly more to users from optimistic cultures compared to pessimistic cultures, while users from optimistic cultures also showed higher adaptation to models than users from pessimistic cultures. Similar reciprocal adaptation patterns were observed in short-term oriented, masculine, and inclusive cultures.

These findings highlight the complex interplay between cultural dimensions and communication adaptation behaviors. The significant patterns observed in how models and users adapt to each other underscore the need for conversational agents to dynamically adjust their interactions based on cultural attributes. Although our analysis necessarily focused on cultures captured within established frameworks, our findings nonetheless provide robust empirical evidence and valuable guidance for developing culturally inclusive AI systems. This adaptation can provide a pivotal mechanism for developing culturally inclusive AI systems that enhance interaction quality and alignment with the human values of diversity, equity, and inclusion on a global scale.

Future work could examine not only whether adaptation occurs, but also the specific conditions under which it is welcomed or resisted, since preferences for convergence or divergence in dialogue may depend on social identity, situational norms, or communicative goals. Moreover, adaptation strategies could be assessed in terms of their effects on downstream outcomes such as trust, rapport, and communicative success, especially in intercultural and cross-cultural interactions where communicative alignment may shape perceptions of respect, authenticity, or competence. In addition, future studies could move beyond national-level frameworks to examine how individual traits such as personality, emotional expression, or prior conversational history influence the perceived appropriateness and impact of accommodation across culturally diverse contexts. Another potential direction is to investigate how different levels of accommodation, including word-level cues and broader discourse features such as politeness or humor, are perceived across cultures, and how they contribute to culturally sensitive accommodation. This development is crucial for creating AI systems that are not only technologically sophisticated but also culturally responsive, ensuring broader applicability and effectiveness across diverse global settings.

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