Communication Accommodation Between Large Language Models and Users Across Cultures (Student Abstract)

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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

The rise of conversational agents powered by large language models (LLMs), such as ChatGPT, is transforming human-computer interaction, making understanding and optimizing the dynamics of digital communication becomes increasingly important. Studies show that style matching, where conversational partners mimic each other's communication styles, significantly boosts satisfaction (van Pinxteren et al. 2023). Rooted in Communication Accommodation Theory (CAT) (Giles, Ogay et al. 2007), this adaptation enhances relational satisfaction by fostering a sense of similarity. Cultural differences also play a role, with research showing that individuals from collectivist cultures, like participants with a Chinese cultural background, adapt more in mixed-culture settings than their American cultural counterparts (Wang and Fussell 2010). As LLMs are deployed globally, understanding how cultural background influences interactions is crucial for designing inclusive, adaptive AI systems.

Building on CAT and cultural communication research, our study examines how human users' cultural backgrounds may affect human-agent conversations. We hypothesize that LLMs may adapt to users' cultural backgrounds and that users may also adjust their communication styles during conversations. We used the PRISM dataset (Kirk et al. 2024), containing 8,011 conversations between 1,500 participants from 75 countries and various LLM-powered agents like GPT-4 and Claude-2. This dataset includes 27,172 interactions, with participants providing sociodemographic details such as age, gender, and birth country, enabling us to study cultural influences on communication. To analyze the impact of national cultures on style matching, we applied Hofstede's cultural dimensions (Hofstede, Hofstede, and Minkov 2005), which categorize countries by behavioral characteristics in an organizational context, mapping each country into four quantiles based on these dimensions. For example, Canada is categorized as high in Individualism (indicating a focus on personal achievements and autonomy) and low in Power Distance (indicating less hierarchical structure), while Japan is categorized as high in Uncertainty Avoidance (indicating a preference for rules and structured environments) and high in Masculinity (indicating a focus on competitiveness and achievement over care and collaboration). To probe how communication styles evolve during interactions, we applied the Linguistic Inquiry and Word Count (LIWC) tool (Pennebaker, Francis, and Booth 2001) to analyze the linguistic, cognitive, and emotional dimensions of conversations. We calculated Language Style Matching (LSM) across 112 LIWC-derived features to quantify the similarity between user and agent communication styles, with scores ranging from 0 (low similarity) to 1 (high similarity). Specifically, we ask the following research questions:

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

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

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

Method

To robustly analyze the effects of cultural dimensions on LSM between user and agent conversation where the same users had multiple interactions with conversational agents, we utilized linear mixed models. Each cultural dimension was treated as a categorical variable with four levels to examine LSM variations between users from different cultural backgrounds. Our model assessed LSM for each conversation i by user j as $\text{LSM}_{ij} = \beta_0 + \beta_1\text{PDI}_{ij} + \beta_2\text{IDV}_{ij} + \beta_3\text{MAS}_{ij} + \beta_4\text{UAI}_{ij} + \beta_5\text{LTOWVS}_{ij} + \beta_6\text{IVR}_{ij} + \epsilon_{ij}$ where cultural dimensions are represented by PDI_{ij} for Power Distance, IDV_{ij} for Individualism, MAS_{ij} for Masculinity, UAI_{ij} for Uncertainty Avoidance, LTOWVS_{ij} for Long-Term Orientation, and IVR_{ij} for Indulgence. The coefficients β_0 through β_6 estimate the impact of each dimension on LSM, and ϵ_{ij} represents the random error for each conversation.

We introduced a variable Turn_{ij} to measure the impact of conversation depth on LSM adaptation over time. We applied Bonferroni corrections to adjust for multiple comparisons. For each LSM variable, we conducted z-tests to determine whether its coefficient for Turn_{ij} significantly differed from the aggregated LSM coefficient. If a significant difference was found after the Bonferroni correction, we assessed the magnitude of this difference to determine whether the communication style converged or diverged over prolonged conversation. Specifically, if the individual coefficient was greater in magnitude than the aggregated coefficient, we interpreted this as evidence of style convergence, indicating increased alignment in communication style over time. Conversely, if the magnitude of the individual LSM coefficient was smaller than the aggregated coefficient, we interpreted this as evidence of style divergence or decreased alignment. This rigorous approach allowed us to assess how specific aspects of communication style were more or less responsive to prolonged interactions compared to the overall communication pattern.

To explore the directionality of communication adaptation—whether users or agents adjust their styles—we applied Granger causality tests. This method assesses whether past communication patterns of one party (e.g., the user) predict the future behavior of the other (e.g., the agent), or vice versa. By examining these causal relationships, we can determine whether users or agents lead the adaptation process in linguistic style, revealing whether communication accommodation is primarily driven by the human participants or the conversational agents in interactions.

Results

RQ1: Do Cultural Dimensions Influence Mutual Adaptation of Communication Styles?

Our analysis of Hofstede's cultural dimensions reveals that the Power Distance Index (PDI) significantly impacts style matching between users and conversational agents. Specifically, users from high PDI countries (e.g., hierarchical societies) exhibited greater linguistic similarity with agents, particularly in expressions of necessity and obligation, such as ”have to” and ”must” ($\beta_1 = 0.1575$, p-value = 0.0003). This suggests that users from these cultures engage in more structured, formal communication, and agents dynamically adapt to these patterns.

RQ2: Communication Convergence or Divergence Over Time

We investigated whether communication styles between users and agents converged or diverged over time using mixed-effects models and Bonferroni-corrected z-tests. Out of 98 significant LSM variables, 59% showed stronger convergence over time, where linguistic similarity increased as conversations progressed. This suggests that LLMs can dynamically adapt to user styles, enhancing conversational flow as interactions continue. However, 41% of the LSM variables demonstrated weaker convergence or divergence, indicating that not all aspects of communication exhibit the same degree of alignment over time, which may reflect differing user expectations or conversational content.

RQ3: Direction of Communication Accommodation

Granger causality tests revealed that conversational agents adapt more frequently to users than vice versa, particularly in cultural dimensions such as Individualism (72% adaptation for IDV 4 vs. 64% for IDV 1, p-value = 0.0144). Conversely, users from lower PDI cultures were more likely to adapt to agents than those from higher PDI cultures ($PDI_1 = 31\%$ vs. $PDI_4 = 25\%$, p-value = 0.0358). Additionally, reciprocal adaptation patterns emerged in optimistic, short-term oriented, masculine, and inclusive cultures, where both agents and users demonstrated mutual adjustment.

Conclusion

This study demonstrates that cultural dimensions significantly influence communication style matching between users and conversational agents. Our findings show that style convergence generally increases over time, with conversational agents dynamically adapting more to users than vice versa. These insights highlight the importance of designing AI systems that are culturally sensitive, enhancing their ability to engage and communicate effectively across diverse cultural contexts.

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