Culture-Specific Verbal Feedback by Robot Tutors: A Cross-Cultural Study in Rwanda and Germany

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***Abstract*— Despite the growing use of social robots in education and their great potential to adapt to individual learners on multiple levels, the aspect of culture is an often-overlooked factor in learner-robot interaction, particularly outside Western and East Asian contexts. This paper presents a cross-cultural study investigating how adapting a robot tutor's feedback style (direct vs. indirect) influences learners' perceptions, trust, and preferences in Rwanda and Germany. Using a 2×2 mixed design, participants interacted with both robot versions and evaluated each separately. Results reveal a main effect of feedback style: across both groups, the indirect-speaking robot was perceived as more socially competent, polite, and warm. We also found cultural differences, with participants in Rwanda evaluating the robot more positively overall than participants in Germany. Additionally, an interaction effect for trust shows that Rwandan participants trusted the indirect robot more, whereas no difference emerged among German participants. These findings highlight the importance of culturally adaptive robot behavior and suggest that aligning communication style with users' cultural expectations can enhance trust and perceived social competence. This work contributes to a more globally inclusive perspective on educational human–robot interaction.**

I. Introduction

Over the past decades, learning with robots has evolved into a major research area, attracting increasing attention from both academia [1] and industry, highlighting their growing relevance as tools to support teaching and learning processes. One key advantage of social robots in this domain lies in their ability to introduce a social dimension otherwise missing in traditional screen-based e-learning environments, which is particularly important given that social interaction between students and teachers has been shown to positively influence academic performance and motivation [2]. In addition, social robots offer the potential to adapt to learners not only at the level of instructional content but also in terms of social interaction [3], enabling more personalized and engaging educational experiences.

While numerous studies have examined various aspects of human-robot interaction in education, an essential dimension has been largely neglected: culture. However, culture plays a fundamental role in human interaction and, by extension, in human–robot interaction (HRI). As argued by Lugrin and Rehm [4], a robot cannot be culturally neutral, and if cultural aspects are not explicitly considered during design, the robot will implicitly reflect the cultural background of its developers. Consequently, there is no universal answer to how a robot should behave in terms of speech, gestures, or proxemics. Cultural competence—the ability of a robot to adapt its behavior and communication style to the cultural norms and expectations of its users—has been identified as a key factor for effective human–robot interaction [5]. This includes not only what a robot does, but also how it provides its services. Particularly in assistive and educational settings, culturally competent robots are expected to increase both acceptability and effectiveness [6]. Similarly, Vernon [7] highlights that successful innovation depends on trust, acceptance, and widespread adoption, all of which are shaped by socio-cultural factors, and argues that social robots must adapt to cultural contexts in order to be effectively deployed. Nevertheless, the current body of research remains limited in scope, with a strong focus on Western and East Asian contexts and a notable lack of cross-cultural studies [8]. As a result, many insights regarding socially appropriate robot behavior and user perception may not generalize across cultural settings but instead reflect the specific contexts in which they were obtained. This limitation is particularly relevant in educational environments, where teaching styles and feedback practices vary significantly between cultures. At the same time, increasing globalization is leading to more culturally diverse classrooms, even within a single country, further amplifying the need for adaptive and culturally aware educational technologies.

To address the lack of cross-cultural studies beyond Western and East Asian contexts and the unclear impact of culturally adapted robots in education, this study examines the effect of a robot's culturally adapted speaking style in a cross-cultural setting at a German and a Rwandan university. Specifically, we investigate how direct versus indirect feedback influences learners' perceptions and acceptance of a robot tutor across cultures, contributing to a better understanding of cultural competence in social robotics and its implications for educational technology design.

II. Theoretical Background

According to Hofstede [9], culture refers to a shared system of socially transmitted values, norms, and behaviors that shapes and guides people's way of life. These cultural patterns are passed down from one generation to the next and distinguish members of one group from those of another. Hofstede et al. [10] also offer one of the most well-established dimensional models, a framework for understanding differences between cultures at the national level. It comprises six dimensions—Power Distance, Individualism, Masculinity, Uncertainty Avoidance, Long-Term Orientation, and Indulgence—each rated from low to

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high. Another particularly influential framework in computer science is based on Hall's [11] anthropological work, which conceptualizes culture through key dimensions such as space, context, and time. Hall further emphasizes the intrinsic link between communication and culture, arguing that "culture is communication and communication is culture" [12, p. 218]. Cultural context strongly influences communication styles. Generally, "people react to how we speak rather than what we say." [13, p. 124]. The construct of communication style has long attracted scholarly attention, leading to numerous classifications and distinctions proposed by different researchers [13]. One of the most widely recognized dimensions is the distinction between direct (low-context) and indirect (high-context) communication [14]. Hall's context dichotomy is particularly relevant, as it frames communication styles along cultural dimensions, especially the distinction between high- and low-context interaction. This dimension describes how much information is conveyed implicitly versus explicitly. Accordingly, low-context communication involves direct communication styles with clear verbal expression, in which meaning is primarily conveyed through words, and information exchange is the central goal. In contrast, high-context communication is more indirect. It relies on implicit cues, such as tone, pauses, and shared contextual understanding, with an emphasis on maintaining harmony and preserving social relationships [15]. In the context of education, these differences become particularly evident in feedback situations: for example, direct communicators prioritize truth over sparing feelings and value honesty above politeness, whereas indirect communicators soften potentially hurtful truths, handle messages to save face, and prioritize politeness over strict honesty. As a result, mismatches between communication styles can lead to fundamental misunderstandings and negative perceptions [15]. Direct feedback may be perceived as rude or inappropriate in indirect cultures, while indirect feedback may be seen as vague, unclear, or unhelpful by individuals from direct communication cultures.

Beyond potential misunderstandings arising from differing communication styles, the Similarity–Attraction Principle [16] suggests that individuals who perceive themselves as similar to their communication partners are more likely to develop positive attitudes toward them. Since individuals from high-context cultures tend to prefer more implicit communication, whereas those from low-context cultures favor more explicit styles, these preferences are—according to Media Equation Theory—likely also transferable to interactions with robots [17]. Indeed, there is already empirical evidence supporting the Similarity Attraction Principle in human–robot interaction (HRI) [18], [19]. Accordingly, social robots that display culture-specific behaviors similar to those of their users are likely to be preferred.

III. Social Robots and Culture

Over the past decades, numerous cross-cultural studies have examined the influence of cultural background on HRI, indicating that individuals from different cultural contexts tend to respond differently to robots and differ in their attitude towards robots [20], in their perception in terms of e.g., trust, comfort, and anthropomorphism [21], and in compliance with these robots [22].

While it is well established that culture influences the perception of and acceptance toward robots, comparatively fewer studies have investigated the design and impact of culturally adaptable robots. People are generally expected to behave in culturally normative ways, and when they do not, it can affect collaboration. Accordingly, research indicates that humans generally prefer agents that conform to the social norms of their own culture and expect robots to adhere to these norms [8]. Robots that act in culturally normative ways are likely to be perceived as having more common ground, being trusted more, and are preferred rather [23] over those that behave in counter-cultural ways. Trovato et al. [24] suggest that humans more readily accept robots adapted to their cultural context. In their study with Egyptian and Japanese participants, two robot versions with culture-specific manners and accents were presented via simulated video. Results showed culture-dependent preferences: Egyptians favored the Arabic-adapted robot and felt discomfort with the Japanese version, while Japanese participants showed the opposite pattern. Participants familiar with both cultures responded positively to both robots. Building on this, Trovato et al. [25] examined cultural closeness using Dutch participants and robot behaviors modeled after German and Japanese cultures. Dutch participants preferred the German robot, indicating that perceived cultural similarity is relative and that even partial similarity can shape robot acceptance. The findings of a recent meta-review by Lim et al. [8] highlight the complex and nuanced relationships between culture and human cognition in HRI contexts. While many studies discuss the preference for robots that are culturally similar to the user, the evidence suggests that the relationship between perceived similarity and robot acceptance is more complex than simple homophily. They highlight that cultural homophily can influence user preferences in some contexts, but individual differences and personal preferences also play a strong role. Overall, robots that demonstrate cultural sensitivity tend to foster greater human acceptance, yet the role of perceived cultural similarity remains an underexplored and highly relevant area for future research [8].

It is important to specify which cultural influences should be implemented in a robot, while distinguishing between different layers of culture that range from explicit manifestations to more implicit, underlying dimensions [4]. Speech, as a highly explicit form of behavior, is a fundamental starting point for implementing cultural adaptation in HRI. Language requirements for robots vary across cultures, as rhetorical cues—beyond factual knowledge—can significantly influence credibility and persuasion [26]. Notably, rhetorical skill had a greater impact on Arabic-speaking participants than on English-speaking participants, underscoring the need for culturally sensitive language design. Rau et al. [19] showed that communication style and culture jointly shape the acceptance of robot recommendations. Compared to Germans, Chinese participants preferred implicit communication and evaluated robots more positively, while no cultural differences were found for explicit communication. Wang et al. [27] showed that human–robot collaboration improves when the robot's communication style aligns with users' cultural norms. Chinese participants responded more positively to implicit communication, while US participants preferred explicit communication, though Chinese participants also reported generally more negative attitudes toward robots.

A notable limitation highlighted in prior work concerns limited cultural diversity among study participants. Currently, there is a strong dominance of studies conducted in Western countries and East Asia and, to a lesser extent, the Middle East. Studies including participants of the African continent are barely existent [8], [6]. Going beyond the traditional Asian–Western cultural dichotomy, a much broader inclusion of cultures is therefore needed to address the relative over- and under-representation of countries in the field [8]. Vernon [7] is among the first to explicitly address an African perspective on culturally competent social robotics. He argues that socio-economic development in African contexts—including the deployment of social robots—must align with local cultural values to be effective. Accordingly, Vernon conceptualizes culturally competent robots as requiring two fundamental capabilities: the ability to interpret human intentions and the capacity to exhibit behavior that is legible and predictable to users, who hold clear expectations regarding appropriate robot behavior. This includes adapting the robot's verbal, nonverbal, and spatial behavior on a cultural dimension. Once the relevant social and cultural norms prevalent in different African contexts are identified, they can be embedded in the robot's behavioral repertoire. This enables social robots to interact in ways that align with locally defined expectations of respectful behavior [7]. For example, the CSSR4Africa project targets the development of culturally sensitive social robots that use cultural knowledge of Rwanda and South Africa [28].

A. Culture in Robots for Education

Education is a key application domain for social robots, increasingly used to support teaching and learning. Social robots can be seen as specialized pedagogical agents—embodied systems guiding or motivating learners through social and instructional interactions [29]. Applications include motor skills, employee training, group work, language learning, and STEM education, often in one-to-one settings for personalized learning. Most research focuses on children, but meta-analyses show potential for all ages [1]. In contrast to traditional computer-supported learning, robots add a social dimension, e.g., by providing interactive feedback, personalized guidance, and motivational support [29]. Social robots can enhance learning by providing real-time feedback, personalized support, and a non-judgmental environment, improving both motivation and engagement, and on a cognitive level, boost learning outcomes and task performance [30]. Adaptation to individual traits such as age, gender, personality, language, or cultural background can further increase their effectiveness [31], [6] and is a key factor of social robots in educational contexts. This includes content adaptation, where instructional material is tailored to the learner's knowledge level or needs, as well as social adaptation [3], in which the robot adjusts its behavior, communication style, and interaction patterns to align with the learner's preferences.

When adapting social robots in education, the learner's cultural background is often overlooked, even though it strongly shapes how robot behavior is perceived and what is considered appropriate [4]. Since teaching behavior varies widely across cultures, social robots in education should similarly adapt their communication and interaction style to fit the learner's cultural expectations. A mismatch between the cultural backgrounds of the robot and the user can lead to misunderstandings, particularly with regard to communication and interaction management behaviors. Conversely, the incorporation of culture-specific cues can enhance user acceptance and facilitate more effective human–robot interaction [4]. Reviewing studies in educational HRI, Bruno et al. [6] found clear cultural differences: Compared to collectivist cultures, individualistic cultures place greater emphasis on personalized learner–robot interactions, preferring one-to-one scenarios, whereas class-based interactions are more common in Asian contexts. Cultures with high power distance favor robots in authoritative roles, such as teachers or tutors, while low power distance cultures prefer robots as collaborative peers. The authors conclude that while social robots are generally expected to respect cultural norms during classroom interactions, it remains unclear which specific dimensions of cultural alignment in HRI are essential.

Speaking styles are an often overlooked aspect in the design of social robots for educational contexts, even though feedback style represents one of the most critical adaptation mechanisms on a social level [32]. Further, individuals tend to trust social robots more when the robots follow communication conventions similar to their own [8]. The present study addresses this gap by focusing on feedback, a fundamental component of the educational context.

This growing body of work demonstrates that adapting a robot's speaking style to users' cultural background is beneficial. Building on this, we extend this research to education, a key application domain of social robots. Moving beyond the typical Western–East Asian focus, this study adopts a cross-cultural design involving students from universities in Rwanda and Germany, thereby contributing to a more globally inclusive perspective.

IV. Contribution

This work investigates the effect of speaking style in feedback delivery within an educational HRI scenario. In doing so, it addresses several gaps in the existing literature, including the limited consideration of cultural factors in educational robotics, the underexplored role of culture in shaping feedback styles, and the lack of representation of African contexts in HRI research. To this end, we conducted a cross-cultural study at a university in Rwanda and a university in Germany. The study employed two robot versions differing in feedback style (direct vs. indirect), with each participant interacting with both versions. Based on prior research on social robots and culture, and theoretical assumptions such as the Similarity-Attraction Principle, we derive the following hypotheses:

- **H1:** Effect of condition. Manipulating the robot's feedback style affects participants' perception of the robot, regardless of cultural background.
- **H2:** Effect of cultural background. Participants' cultural background affects their perception of the robot and their preferences, regardless of the robot's feedback style.
- **H3:** Interaction effect. Participants studying in Rwanda are expected to show a stronger preference for the indirect-speaking robot, whereas participants studying in Germany are expected to prefer the direct-speaking robot.

V. Robot-supported Learning Environment

We designed a learning environment consisting of a tablet-based learning unit and a fully autonomous robot tutor. While the learning content on the tablet was identical for all participants, we designed two versions of the robot that differed in their feedback style.

The learning procedure consists of two phases. In the first phase, participants complete a time-limited self-study unit in which they review the instructional content on a tablet. During this phase, learners can freely navigate through the learning materials, allowing them to move forward and backward between pages according to their individual learning strategies. In the second phase, the robot conducts a quiz on the previously studied content and provides feedback on the participants' responses. In contrast to the flexible navigation during the self-study phase, the sequence and structure of the quiz interaction with the robot are predefined and follow a fixed order. This ensures a consistent interaction flow and allows for controlled comparison of the robot's feedback styles across participants.

The Pepper robot was selected as the interactive tutor. Its integrated tablet enables the presentation of learning materials and supports reliable, robust touch-based interaction, which is preferable in this context, as speech recognition can still be error-prone. The robot communicates with learners through multimodal channels, including synthesized speech (text-to-speech), gestures, and visual feedback. These modalities are used to enhance the social dimension of the interaction and to create a more engaging learning experience.

A. Learning Materials

The learning materials address the usability of computer systems and include, for example, topics such as heuristic evaluation and various usability testing methods. This topic was selected because neither of the two participant groups had prior knowledge of this area in their academic studies, yet it holds potential relevance for both groups. The learning environment was implemented on a tablet using PowerPoint. Individual slides were populated with written and graphical content, and arrow buttons were integrated to enable navigation between the slides. The learning materials were divided into two instructional units, each lasting approximately seven minutes. They were designed to be of comparable difficulty, developed by a subject-matter teacher, and structured to be comfortably manageable within a seven-minute learning period.

B. Social Robot Quizmaster

As noted above, the Pepper robot was chosen as the interactive tutor and served as the central interface for the quiz interaction. To enhance the naturalness of the interaction, the robot exhibited lifelike behaviors throughout the session. These included idle animations such as blinking, subtle breathing movements, and small background motions. The interaction language was adapted to the participants' academic environment, using either English or German depending on the primary language of instruction at the university. Technically, the robot's behavior was implemented using the JavaScript SDK together with an HTML-based tablet interface. The system builds upon robot-jumpstarter, a utility library developed by SoftBank Robotics Europe SAS by Emile Kroeger,[1] and was further extended by the authors to support the experimental interaction design.

The quiz consisted of seven questions covering the previously studied learning material. Different question formats were used to increase variety and to assess different forms of knowledge recall. These included single-choice questions, multiple-choice questions, cloze tasks with drop-down answer selections, and open text gaps. In addition to the robot's verbal feedback, visual feedback was simultaneously presented on the integrated tablet.

For each response, the robot provided feedback depending on whether the answer was correct or incorrect. Correct responses were followed by positive reinforcement, whereas incorrect responses triggered corrective feedback indicating that the answer was not correct and providing the right solution. Varying the robot's speaking style in formulating this feedback was the primary experimental manipulation. When an answer was incorrect, the robot responded either with direct or indirect feedback formulation. In the direct condition, the robot explicitly stated that the response was incorrect (e.g., "Unfortunately, that was wrong"). In the indirect condition, the feedback was phrased in a softer and more mitigated manner (e.g., "Not quite, but we are getting there"). In contrast, positive feedback for correct answers offered limited room for stylistic variation and was therefore largely similar across both speaking-style conditions. Regardless of the feedback style, the robot always provided the correct answer after each question to ensure that all participants received the same information. To ensure authenticity and cultural appropriateness, the speaking styles in both language

[1] https://github.com/aldebaran/robot-jumpstarter?tab=readme-ov-file

versions were evaluated by individuals familiar with the respective linguistic and cultural contexts. Based on this evaluation, formulations were reviewed and, where necessary, adjusted to ensure that the feedback sounded natural and culturally appropriate.

VI. User Study

We conducted a user study on two different continents: Africa and Europe. The study in Africa took place at Carnegie Mellon University Africa (CMU-Africa) in Rwanda, while the European study was conducted at Julius-Maximilians-Universität (JMU) Würzburg in Germany. The study employed a 2×2 mixed design, with robot speaking style (direct vs. indirect) and participants' university location (Rwanda vs. Germany) as factors. Participants interacted sequentially with both versions of the robot in random order and evaluated each version separately after the respective interaction.

A. Measurements

To explore potential differences in participants' trust in the robot, we used the subscale Trust of the Almere Questionnaire [33] (rated from '1 – totally disagree' to '5 – totally agree'). Further, we used the subscale Perceived Sociability from the same questionnaire to assess whether the robot is perceived to perform social behavior. Assessing perceived warmth and competence of the robot, the respective subscales of the RoSAS [34] were used, including 12 items with adjectives rated on a scale from '1 - definitely not associated' to '9 - definitely associated'. The robot's politeness was measured using three items developed by [35] to assess the perceived level of politeness in speech. Lastly, we asked participants which of the two robots they interacted with they would prefer for future interactions, and provided a free-text field where they could explain their choice. Additionally, we collected demographic information such as age, gender, nationality, cultural background, and prior experience with the robot by self-assessment, and provided a free-text field for participants to share any further comments about the study.

B. Participants

In total, N = 44 students participated in the study. As the robot's speaking style was only perceptible during corrective feedback, only participants who made at least two errors per condition were included in the final analysis, ensuring sufficient exposure to the manipulated feedback style. This results in N = 36 valid data sets, from which n = 18 were students of the CMU-Africa, Rwanda (2 female, 14 male, 2 without disclosure) and n = 18 students of the JMU Würzburg, Germany (14 female, 4 male). The mean age of the CMU-Africa students was M = 25.82 (SD = 2.30) and of the JMU students M = 20.39 (SD = 1.50). While the JMU sample consists solely of students of German nationality, the CMU-Africa sample includes multiple nationalities: Nigerian (7), Ethiopian (4), Rwandan (2), Cameroonian (2), Ghanaian (1), and Sudanese (1), with one participant not disclosing their nationality.[2] Regarding prior experience with the robot, n = 10 students in the CMU-Africa sample indicated no prior experience with the robot, while n = 5 reported substantial experience and had already programmed it. Two students had minimal exposure, having either seen it on TV or interacted with it once. Among the JMU students, n = 12 indicated no prior knowledge, and n = 6 had seen the robot on TV or in real life. However, none had prior experience interacting with or programming it. All participants had no prior knowledge of the learning topic.

C. Procedure

The experimental setups at both locations (CMU-Africa and JMU Würzburg) were designed to be as similar as possible in order to ensure comparable conditions. Each setting consisted of a room with a table on which a tablet was placed for the learning task, a computer for the questionnaire, and a robot positioned nearby. This arrangement allowed participants to easily switch from learning on the tablet to interacting with the robot. The experimenter was present in the room but remained behind a partition wall to minimize potential disturbances during the session.

The procedure was identical at both locations. Participants interacted with both versions of the robot (direct and indirect communication), one after the other, with the order randomized across participants. The difference between the two versions of the robot was not communicated to the participants. To enable participants to distinguish between the robots when later indicating their preferred one, the two versions were assigned different names: Alex and Tony. At the beginning of the session, participants signed an informed consent form. They then started with learning unit A on a tablet, for which they had seven minutes. After completing the learning phase, participants engaged in a quiz with the robot about the material they had just learned. Depending on the randomized condition, they interacted either with the direct or the indirect version of the robot. The quiz interaction lasted approximately five minutes. Following this, participants completed a short questionnaire on a laptop, which took about three minutes. Afterward, participants proceeded to the second round of the experiment. They first worked on learning unit B on a tablet for seven minutes. This was again followed by a quiz with the robot, this time using the other version of the robot (direct or indirect). Participants then completed another short questionnaire. In total, the experimental session lasted approximately 30 minutes.

VII. Results

We conducted a 2 (University location Rwanda/Germany) × 2 (robot version direct/indirect) mixed ANOVA for each scale of the questionnaires. All analyses were computed using *JASP* version 0.19.1 and a significance level of .05.

[2] While it must be borne in mind that Africa is a continent comprising fifty-four countries and many different cultures, it is nevertheless true that people from Sub-Saharan Africa countries, including all the CMU-Africa sample, generally adhere to the collectivist African philosophy of Ubuntu [36], and this is reflected in the manner in which their peoples interact [7].

A. Perception of the Robot

Trust. Regarding trust, a mixed ANOVA showed no significant main effect of culture, $F(1, 34) = 0.16$, $p = .689$, $\eta_p^2 = .004$, and a marginally significant main effect of robot version, $F(1, 34) = 3.97$, $p = .054$, $\eta_p^2 = .019$ in favor of the indirect robot. However, the interaction between culture and robot version was significant, $F(1, 34) = 7.06$, $p = .012$, $\eta_p^2 < .034$, with the African students rating the indirect robot significantly higher than the direct robot. Descriptive values can be found in Table I.

Robot Version	Location	N	Mean	SD
Direct	Rwanda	18	3.25	0.90
Direct	Germany	18	3.69	0.89
Indirect	Rwanda	18	3.83	0.54
Indirect	Germany	18	3.61	1.18

TABLE I

DESCRIPTIVE STATISTICS FOR TRUST ACROSS THE EXPERIMENTAL CONDITIONS.

Perceived Sociability. Looking at perceived sociability, a mixed ANOVA revealed no main effect of culture, $F(1, 34) = 1.96$, $p = .171$, $\eta_p^2 = .04$, but a significant main effect of robot version, $F(1, 34) = 8.30$, $p = .007$, $\eta_p^2 = .053$, with the indirect robot being rated as more sociable than the direct robot. The interaction between culture and robot version was also not significant, $F(1, 34) = 0.13$, $p = .437$, $\eta_p^2 < .004$. Descriptive values can be found in Table II.

Robot Version	Location	N	Mean	SD
Direct	Rwanda	18	3.61	0.77
Direct	Germany	18	3.43	0.59
Indirect	Rwanda	18	4.00	0.37
Indirect	Germany	18	3.65	0.78

TABLE II

DESCRIPTIVE STATISTICS FOR PERCEIVED SOCIABILITY ACROSS THE EXPERIMENTAL CONDITIONS.

Warmth. Concerning warmth, a mixed ANOVA showed a significant main effect of culture, $F(1, 34) = 18.99$, $p =< .001$, $\eta_p^2 = .299$, and a significant main effect of robot, $F(1, 34) = 23.73$, $p =< .001$, $\eta_p^2 = .068$. CMU-Africa students perceived the robot as more warm than JMU Würzburg students, and in general, both groups rated the indirect robot as more warm than the direct robot. The interaction between culture and robot version was not significant, $F(1, 34) = 0.11$, $p = .738$, $\eta_p^2 < .001$. Descriptive values can be found in Table III.

Competence. Regarding competence, a mixed ANOVA revealed a significant main effect of culture, $F(1, 34) = 8.47$, $p = .006$, $\eta_p^2 = .178$, with CMU-Africa students rating the robot as more competent than JMU Würzburg students independently of condition. The main effect of robot version was not significant, $F(1, 34) = 2.05$, $p = .162$, $\eta_p^2 = .006$. The interaction between culture and robot version was also not significant, $F(1, 34) = 0.24$, $p = .630$, $\eta_p^2 < .001$. Descriptive values can be found in Table IV.

Robot Version	Location	N	Mean	SD
Direct	Rwanda	18	6.38	1.14
Direct	Germany	18	4.62	1.72
Indirect	Rwanda	18	7.31	0.89
Indirect	Germany	18	5.43	1.53

TABLE III

DESCRIPTIVE STATISTICS FOR WARMTH ACROSS EXPERIMENTAL CONDITIONS.

Robot version	Location	N	Mean	SD
Direct	Rwanda	18	7.69	0.95
Direct	Germany	18	6.84	1.27
Indirect	Rwanda	18	7.92	0.81
Indirect	Germany	18	6.95	0.90

TABLE IV

DESCRIPTIVE STATISTICS FOR COMPETENCE ACROSS EXPERIMENTAL CONDITIONS.

Politeness. For politeness, a mixed ANOVA revealed no main effect of culture, $F(1, 34) = 0.68$, $p = .415$, $\eta_p^2 = .018$, but a significant main effect of robot version, $F(1, 34) = 8.14$, $p = .007$, $\eta_p^2 = .018$, with the indirect robot being rated as more polite than the direct robot. The interaction between culture and robot version was also not significant, $F(1, 34) = 0.46$, $p = .503$, $\eta_p^2 = .001$.

B. Preference for the Robot Version

A chi-square test of independence examined the association between University location (Rwanda vs. Germany) and robot preference (direct, indirect, no preference). The analysis revealed no significant association between the variables, $\chi^2(2, N = 35) = 4.55$, $p = .103$, Cramér's $V = .36$ (lower N because of one missing value due to technical issues). The exact frequencies of each preference are shown in Table V.

Location	Direct	Indirect	No preference
Rwanda	3	7	7
Germany	3	13	2

TABLE V

FREQUENCIES OF ROBOT PREFERENCE BY ORIGIN.

When asked to justify their robot preference, participants most frequently mentioned that the indirect robot was perceived as more emotionally expressive ($n = 6$) and friendlier ($n = 4$). Specifically, participants attributed greater compassion, empathy, and the ability to emotionally engage to the indirect robot.

The direct robot also had supporters who explicitly valued its direct communication style. Participants described this preference as follows: "I find that I learn better when it is uncomfortable to make a mistake; with Tony (the direct robot), this discomfort was clearly more pronounced." Another participant stated, "I would rather the robot tell me I am wrong than make me feel I may be right. Since it is not subjective, letting me know I am wrong is better than letting me feel I had another perspective. This feels underhanded and deceptive."

VIII. Discussion

In this paper, we present a cross-cultural study conducted at a Rwandan and a German university to investigate how students perceive the feedback style of a social robot tutor, particularly when it aligns with or contradicts their cultural background. The results reveal several noteworthy main and interaction effects. Across both cultural groups, the indirect robot was consistently evaluated more positively on key social dimensions: it was perceived as more socially competent, more polite, and warmer than the direct robot, confirming **H1**. These findings suggest that an indirect communication style may generally enhance the perceived social appropriateness of robot tutors, independent of the learners' cultural background.

In addition, significant main effects of culture were observed, supporting **H2**. CMU-Africa students evaluated the robot as warmer and more competent overall compared to JMU Würzburg students, regardless of the robot's communication style. This indicates that baseline perceptions of social robots may differ across cultural contexts, potentially reflecting differing expectations, prior experiences, or cultural norms related to social interaction, which is consistent with previous studies (e.g., [19], [27], [26]).

Furthermore, the analysis revealed an interaction effect for trust, partly supporting **H3**. CMU-Africa students reported higher levels of trust in the indirect robot compared to the direct robot, whereas no such difference was found among German students. This suggests that cultural background may moderate how communication style influences trust in human–robot interaction, with indirect communication being particularly relevant for fostering trust among CMU-Africa students. Finally, no statistically significant overall preference for either robot version was found. However, descriptive patterns indicate that German students more frequently preferred the indirect robot, while CMU-Africa students equally reported no preference or a preference for the indirect robot. It is somehow unexpected that German participants—despite their typically direct communication culture—showed a preference for indirect feedback. One possible explanation could be that indirect communication may be more attractive in short-term interactions with unknown social entities, while long-term preferences in learning with a robot tutor could differ. A review of the open-ended responses supports this interpretation: participants who preferred the direct robot often cited improved learning as their reason, whereas those who chose the indirect robot tended to do so for emotional or relational reasons. The observed interaction effect is consistent with established findings in cross-cultural communication and human–robot interaction as well as the Similarity-Attraction Principle. Further, our results align with prior work showing that participants with high-context cultural backgrounds prefer implicit communication and evaluate robots more positively in terms of likability, trust, and credibility, while no cultural differences emerge for explicit communication [19]. Particularly with respect to trust, the higher trust in the culturally similar robot is not surprising, as cultural similarity constitutes an important personal factor in fostering trust [37]. CMU-Africa participants having more trust in a robot with a similar speaking style highlights the importance of culturally adaptive robot behavior, particularly as trust is a key factor for successful innovation [7].

The absence of significant effects for other measures may be explained by the short interaction duration, which might not have been sufficient for participants to fully perceive and internalize differences in speaking style. The short interaction duration further limits conclusions about whether the observed effects would persist in long-term human–robot interactions. Additionally, the composition of the sample may have influenced the results: the sample of CMU-Africa students comprises individuals from several African countries, potentially blending different communication norms and making it difficult to attribute observed effects to a single cultural style. Although collectivistic cultures mainly use an indirect communication style, it may vary across regions within African countries, limiting our ability to account for such differences. Further, instructions for CMU-Africa students were not conducted in the students' native languages, but in English, which is the university's teaching language. We aim to address these limitations in future research.

In summary, we consider these results highly promising, as we found support for all examined effects (location, robot version, and interaction), despite the small sample size. This work is a pioneering study that intentionally provides valuable initial data in the challenging field of cross-cultural HRI research beyond the typically investigated Western and East Asian populations. The rarity of such datasets underscores the significance of these early-stage findings and highlights their potential to inform and guide future research in underrepresented cultural contexts.

IX. Conclusion

In this contribution, we investigate how a social robot tutor's speaking style (direct vs. indirect), whether culturally aligned with or different from participants' backgrounds, affects students in a cross-cultural study involving universities in Rwanda and Germany. CMU-Africa students rated the robot more positively overall in terms of warmth and competence, regardless of speaking style. However, they reported higher levels of trust in the indirect-speaking robot—reflecting their own cultural communication style—compared to the direct-speaking robot. In contrast, German participants showed no significant differences between the two conditions. This study focused on the dimension of feedback style. While examining a single dimension is a valuable starting point, further investigation and the exploration of additional dimensions are promising. Building on this, we provide a first step toward implementing, integrating, and evaluating such approaches in cross-cultural contexts. The results inform the design of social robots for educational settings, highlighting the importance of cultural adaptiveness. By incorporating a more diverse cultural perspective, this study contributes to the development of culturally adaptive social robots in education and supports greater inclusion of cultures in HRI research.

X. Declaration of Use of Generative AI

The authors used ChatGPT (OpenAI) to improve the manuscript's clarity and writing style. All content was subsequently reviewed and edited by the authors, who take full responsibility for the final manuscript.

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