Factors Influencing Trust in Human-Robot Interaction: A Case Study

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Abstract. The goal of this article is to investigate factors that influence trust in Human-Robot Interaction (HRI), focusing on communication variables and social behaviors that might shape the users' perception of robots. The research was conducted within the I-CATER project, which explores social robots in work environments. A questionnaire combining the Godspeed Questionnaire Series (GQS) and the Big Five Inventory-10 (BFI-10) was created to assess trust perceptions in different scenarios featuring different communication settings in error situations, initiatives to start a task, and varying facial expressions. Data analysis with the Friedman and Wilcoxon tests revealed that justifications and apologies improve perceptions of likeability and intelligence, while dynamic facial expressions increase perceptions of anthropomorphism, likeability, and animacy. Although age, occupation in the technology field, and ownership of robotic equipment at home did not significantly correlate with trust dimensions, weak gender correlations indicated that male participants tended to rate trust-related dimensions lower. The study contributes to the understanding of how robot communication and social behaviors influence trust in HRI.

Keywords: Trust in Human-Robot Interaction · Godspeed Questionnaire Series · Nonparametric Analysis · Correlation Analysis

1 Introduction

The evolution of robotics has transformed the relationship between humans and robots, promoting a shift in perception that positions robots as active partners in both daily life and work environments. As human-robot teams increasingly emerge across diverse settings [1,19], the success of these collaborations hinges on a fundamental element: trust. Trust, defined as the acceptance of vulnerability associated with relying on others [15,19,20], is a dynamic construct that can fluctuate over time, particularly in response to trust violations, such as errors made by robots [7,8].

Researchers have explored numerous strategies to mitigate the negative impacts of these violations, including trust repair strategies such as apologies,

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denials, explanations, and promises [11]. At the core of this exploration is the realization that trust is deeply influenced by users' perceptions of robots as trustworthy agents capable of fulfilling their roles effectively [4]. This multidimensional nature of trust encompasses factors such as reliability, robustness, familiarity, comprehensibility, and the ability to explain intentions—all critical for fostering positive human-robot interactions (HRI) [3,12].

The robustness of a robot significantly influences its perceived status, impacting whether it is viewed as a lifelike entity or merely a machine [3]. Research by Fu et al. (2023) [9] highlights the critical role of emotional expressiveness in human-robot collaboration, demonstrating that a robot's happy facial expressions and appropriate gaze direction markedly enhance perceived intelligence and teamwork effectiveness. Their findings revealed that collaboration improved notably when the robot initially displayed a cheerful expression, and participants rated the robot as more intelligent when it showcased positive emotions at the conclusion of the interaction. These results underscore the importance of anthropomorphic design and the ability to convey emotions in fostering trust in robotic systems.

Robots must employ effective verbal and non-verbal communication systems, that improve comprehensibility and influence users' impressions of likeability, intelligence, and animacy. Intelligence, whether cognitive or emotional, is vital in this communication process, as it affects how information is conveyed and interpreted, fundamentally shaping interactions [16]. Furthermore, likeability and warmth-based trust have been shown to positively impact users' intentions to utilize robots in the future [4].

Moreover, there is evidence suggesting that personality significantly influences perceptions and interactions with robots [13]. The Big Five personality model, which encompasses dimensions such as extraversion, agreeableness, conscientiousness, neuroticism, and openness, serves as a valuable framework for understanding individual differences in user interactions with robotic systems [17]. Emerging evidence indicates that user personality traits and attitudes correlate with various social outcomes in human-robot interaction (HRI). For example, Elson et al. (2020) [6] found that individuals with high openness personality traits are more likely to trust humanoid robots. Additionally, extraversion has been shown to affect user impressions of robots, further illustrating the importance of personality in shaping HRI dynamics [13].

Given these dynamics, further studies are needed to explore user perceptions and trust in HRI. This research aims to collect data to explore how sociodemographic characteristics, previous experiences with robots, and personality traits correlate with trust. It will investigate how robot communication following mistakes affects perceived intelligence and likeability, assess the impact of the robot's initiative on its animacy, likeability, and perceived intelligence, and analyze how facial expressions influence factors such as anthropomorphism, animacy, and likeability. Through these insights, we seek to further understand the interplay between user characteristics and robot behaviors to foster trust and effective collaboration in human-robot partnerships.

The remainder of this paper is organized as follows: In the Sect. 2, we present the guiding hypotheses and the experimental framework, including the video scenarios of the HRI and the overall questionnaire. The Data Collection and Analysis section outlines the processes involved in data acquisition and the subsequent analytical techniques used. In the Results section, we present the findings of our study. Finally, the Conclusion section summarizes the key insights, highlights the study's contributions to the field, and suggests directions for future research.

2 Research Hypotheses and Experimental Design

This study employed a structured video-based methodology to evaluate trust-related factors in HRI. These videos were a key component of a comprehensive questionnaire designed to assess factors influencing trust in HRI. The questionnaire incorporated the Godspeed Questionnaire Series (GQS) [2] to measure dimensions related to trust, complemented by the Big Five Inventory-10 (BFI-10) [14] to assess participants' personality traits. The GQS focuses on five sections: Anthropomorphism, Animacy, Likeability, Perceived Intelligence, and Perceived Safety. In this study, we evaluated the first four, excluding Perceived Safety, as participants' assessments were based solely on video observations, which do not provide sufficient context to meaningfully evaluate safety-related perceptions. Regarding the BFI-10, since personality is not the main focus of this study and to minimize the length of the questionnaire for participants, we opted for the 10-item version. Both questionnaires (GQS and BFI-10) utilize a Likert scale to assess participants' responses, allowing for the measurement of perceptions and attitudes in a nuanced manner.

Sawyer, a robot featured in prior studies by Cunha et al. (2020) [5] and Wojtak et al. (2021) [18], was selected for its established role in HRI research (Fig. 1).



Fig. 1. Image from one of the produced videos for the study.

The objective of the first set of videos was to assess how Sawyer's communication strategies impact trust, specifically examining participants' perceptions in various scenarios. In each scenario, Sawyer's task was to pass a yellow column, but he made an error by dropping it prematurely. Each of the three videos illustrated a different response from Sawyer following the mistake:

Scenario 1.1: The robot apologizes for the committed error without offering an explanation for it.
Scenario 1.2: The robot offers a justification for the error and then apologizes.
Scenario 1.3: The robot justifies the error but does not apologize.

After each video, participants evaluated Sawyer's intelligence and likeability. This set of scenarios aimed to test the following research hypotheses (RH), inspired by Cameron et al. (2021) [4]:

RH1 Apologizing increases participants' perceptions of the robot's likeability.
RH2 Explaining the error improves participants' perceptions of the robot's intelligence.
RH3 Apologizing without providing an explanation leads to lower perceived intelligence compared to scenarios that include an explanation.

The second set of videos explored how Sawyer's initiative influences trust. In each scenario, Sawyer attempts to pass a yellow column, with varying levels of initiative:

Scenario 2.1: The robot begins the task without any prior communication.
Scenario 2.2: Before starting the task, the robot asks for permission to proceed and, after receiving approval, executes the task.
Scenario 2.3: The robot clearly communicates its intentions before executing the task.
Scenario 2.4: The robot only initiates the task after receiving an explicit request.

Participants' perceptions of Sawyer's animacy, likeability, and intelligence were assessed after each video. Hypotheses tested in this set include:

RH4 Lack of communication decreases participants' perceptions of the robot's animacy, likeability, and intelligence.
RH5 Requesting permission before acting increases participants' perceptions of the robot's animacy, likeability, and intelligence.
RH6 Clearly communicating the robot's intentions before executing the task increases participants' perceptions of robot's animacy.
RH7 The robot interacting with the user before taking action increases participants' perceptions of robot's intelligence and likeability.

The three last video scenarios presented Sawyer's facial expressions under different conditions, following each with questions on anthropomorphism, animacy, likeability, and intelligence:

Scenario 3.1: The tablet that simulates the robot's face is turned off, displaying a black screen, with no facial expression.
Scenario 3.2: The robot's face is displayed on the tablet but with no eye movement, keeping the facial expression static.
Scenario 3.3: The robot's face, displayed on the tablet, includes eye movement, making the facial expression more dynamic and realistic.

The objective here is to evaluate how the robot's facial expressions affect trust, considering the formulated hypotheses:

RH8 The lack of facial expression reduces participants' perceptions of the robot's anthropomorphism, animacy, and likeability.
RH9 Even without eye movement, displaying a face on the tablet increases participants' perceptions of the robot's anthropomorphism, animacy, and likeability compared to when no facial expression is visible.
RH10 Eye movement increases participants' perceptions of the robot's anthropomorphism, animacy, and likeability.

3 Data Collection and Analysis

Data was collected via Google Forms between April and June 2024, with the questionnaire offered in both English and Portuguese versions. To recruit participants, institutional emails were sent to faculty members, students, and staff, and the questionnaire was also promoted through social media. Printed QR codes were distributed to enable quick and direct access to the questionnaire via mobile devices.

After the data collection period, the first step in data analysis involved cleaning and preprocessing the dataset. All Portuguese responses were translated into English to ensure consistency in data analysis. The dataset was imported into R software for further analysis. Variables were appropriately formatted for analysis, and participants were asked to indicate the exact time they completed the questionnaire. To ensure thoughtful engagement, only participants who spent at least 15 min completing the questionnaire were included in the analysis—reflecting the minimum time needed to view all videos and respond adequately. Additionally, demographic factors such as age, gender, and occupation were collected.

In the preliminary analysis, descriptive analysis was conducted, and the quality and reliability of the questionnaire were assessed using Cronbach's Alpha test, ensuring that the measurement scales were valid and consistent. Point-biserial correlation coefficient and Kendall's tau coefficient were calculated to assess the strength and direction of relationships. The point-biserial correlation was used to analyze the relationships between binary variables and the scores for each GQS dimension obtained in each scenario. Meanwhile, Kendall's tau was employed to examine the relationships between age and the scores for each GQS dimension in each scenario. Radar charts were then employed to visually compare GQS dimension scores across scenarios, providing an intuitive overview of perception

trends. Non-parametric statistical tests were applied for further analyses, specifically Wilcoxon tests utilized to identify specific group differences. A significance threshold of $p < 0.05$ was adopted for all inferential statistical analyses.

4 Results

4.1 Participant Demographics

Among the 114 participants who completed the questionnaire, 26 responses were excluded from the analysis—one due to the participant being under 18 years old and 25 because they finished the questionnaire in less than 15 min. Table 1 presents descriptive statistics detailing the demographic characteristics of the study participants, including age, gender, main occupation, technology field affiliation, and possession of robotic equipment at home.

Table 1. Descriptive statistics presenting the number of cases (n) and the percentage (%) for each category of the analyzed variables.

Variables	n	%
Age Group		
18 to 24 years	23	26.14
25 to 34 years	16	18.18
35 years or older	49	55.68
Gender		
Female	44	50
Male	44	50
Other	0	0
Main Occupation		
Student	29	32.95
Employed (full-time or part-time)	45	51.14
Other	14	15.91
Technology Field		
Yes	37	42.05
No	51	57.95
Robotic Equipment at Home		
Yes	33	37.5
No	55	62.5

The sample is balanced by gender, with 50% identifying as female and 50% as male. The age distribution shows that 55% are 35 years or older, 18% are between 25 and 34 years old, and 26% are 18 to 24 years old. In terms of occupation, participants are predominantly employed, whether full- or part-time (51%), or are students (33%), while 16% indicated other occupations. Regarding affiliation with the technology field, 42% are part of this sector. Lastly, approximately 63% of the participants do not have robotic equipment at home.

4.2 Reliability of Questionnaires

The value obtained for α for the GodSpeed Questionnaire was 0.98, indicating an excellent internal consistency of the data. In contrast, the BFI questionnaire resulted in a low Cronbach's alpha of 0.192, suggesting that individuals in the sample may have diverse or differing responses. This variation could arise from different interpretations of the questionnaire items or inherent differences in personality traits. This diversity can lead to inconsistencies in the data, making it challenging to reliably assess the targeted associations. Consequently, we have excluded the results of the BFI questionnaire from further analysis.

4.3 Correlation Analysis

Age, being in the technology field and possession of robotic equipment at home did not show significant correlations with GQS (Table 2). However, some positively weak but statistically significant correlations ($p < 0.05$) were identified for gender, indicating that male individuals tended to rate intelligence, likeability, and animacy lower in some scenarios.

4.4 Influence of Error Responses on Perceptions

In the first scenario, which examines the robot's response to errors, Scenario 1.2—where the robot provides a justification for its error followed by an apology—achieved the highest scores in both perceived intelligence and likeability. This contrasts with Scenario 1.1, where the robot offers only an apology and is rated higher for likeability, and Scenario 1.3, in which the robot solely justifies its error and is perceived as demonstrating greater intelligence. Median values are also presented in Table 3, along with the results of the Wilcoxon test, which indicate significant differences between the scenarios. These findings are illustrated in Fig. 2, which compares perceived intelligence and likeability across the different scenarios based on aggregated Likert scale scores.

4.5 Influence of Verbal Interaction on Perceptions

In the second set of scenarios, those that involved verbal interaction consistently achieved the highest scores. Notably, Scenarios 2.2 and 2.4, which both featured human-robot communication, demonstrated elevated scores across animacy, perceived intelligence, and likeability. Scenario 2.3, where the robot communicates its intentions prior to taking action, maintained a similar pattern of high scores, ranking particularly high in animacy, followed by perceived intelligence and likeability. Conversely, Scenario 2.1—which did not involve prior communication—recorded the lowest scores, emphasizing the critical role of communication in shaping perceptions of animacy, intelligence, and likeability. These differences are supported by the results of the Wilcoxon rank sum tests presented in Table 4. The p-values indicate statistically significant differences ($p < 0.05$) in all assessed dimensions (animacy, intelligence, and likeability) when comparing Scenario 2.1

Table 2. Correlation coefficients: Kendalls' tau for Age and Point-Biserial correlation coefficients for Gender, Technology field, and Robotic equipment, relating to Anthropomorphism, Animacy, and Likeability in different scenarios (SC).

	Age	Gender	Technology field	Robotic equipment at home
SC 1.1 - Likeability	−0.01	0.10	−.007	0.01
SC 1.1 - Intelligence	−0.11	0.11	−0.06	.008
SC 1.2 - Likeability	−0.04	**0.22**	−0.05	0.11
SC 1.2 - Intelligence	0.00	**0.25**	−0.11	0.03
SC 1.3 - Likeability	0.13	0.04	0.02	0.13
SC 1.3 - Intelligence	0.00	**0.20**	−0.08	0.02
SC 2.1 - Animacy	.007	0.17	−0.02	−0.12
SC 2.1 - Intelligence	−0.10	0.16	−0.03	0.15
SC 2.1 - Likeability	−0.10	0.02	−0.07	0.02
SC 2.2 - Animacy	0.02	**0.26**	−0.04	−0.16
SC 2.2 - Intelligence	−.001	0.17	−0.04	0.01
SC 2.2 - Likeability	−0.03	0.16	−0.02	0.01
SC 2.3 - Animacy	−0.03	0.17	0.06	−0.13
SC 2.3 - Intelligence	−0.01	**0.22**	−0.07	−0.05
SC 2.3 - Likeability	−0.04	0.12	−0.11	−0.05
SC 2.4 - Animacy	0.04	0.07	0.02	−0.02
SC 2.4 - Intelligence	0.01	0.06	−0.06	0.01
SC 2.4 - Likeability	−.002	−.005	0.02	0.10
SC 3.1 - Anthropomorphism	−0.07	0.05	0.10	−0.06
SC 3.1 - Animacy	−0.16	0.05	0.16	−0.12
SC 3.1 - Likeability	−0.02	−0.17	−0.04	0.07
SC 3.2 - Anthropomorphism	−0.07	0.09	0.07	−0.05
SC 3.2 - Animacy	−0.16	0.12	0.13	−0.07
SC 3.2 - Likeability	−0.14	0.08	−0.04	0.04
SC 3.3 - Anthropomorphism	−0.13	0.07	0.12	−0.10
SC 3.3 - Animacy	−0.18	0.13	0.18	−0.16
SC 3.3 - Likeability	−0.16	0.12	0.06	−0.06

Significant p-values are indicated in bold.

Table 3. Median scores and Wilcoxon test results for GQS dimensions across scenarios (SC) 1.

GQS dimension	Median			SC 1.1 vs 1.2	SC 1.2 vs 1.3	SC 1.1 vs 1.3
	SC 1.1	SC 1.2	SC 1.3			
Likeability	18.0	20.0	15.0	**p<.001**, W=277[a]	**p<.001**, W=116.5[b]	**p<.001**, W=640[c]
Intelligence	16.0	20.0	17.0	**p<.001**, W=213.5[a]	**p<.001**, W=213.5[b]	**p=.022**, W=1016[d]

[a] H1: SC 1.1 < SC 1.2, [b] H1: SC 1.3 < SC 1.2, [c] H1: SC 1.3 < SC 1.1, [d] H1: SC 1.1 < SC 1.3.

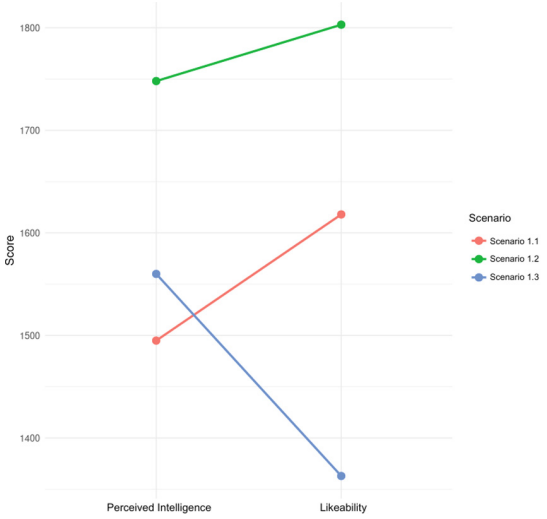

Fig. 2. Comparison of Perceived Intelligence and Likeability characteristics in Scenario 1. The graph is based on the sum of the Likert scale scores for each component of the scenario.

against other scenarios. Specifically, Scenarios 2.2 and 2.3 displayed significantly higher scores compared to Scenario 2.1, confirming that verbal interaction positively influences a robot's perceived characteristics. These results are further depicted in Fig. 3, which illustrates a comparison of these characteristics across the different scenarios based on the aggregate Likert scale scores.

4.6 Influence of Facial Expressions on Perceptions

In analyzing the third scenario, the condition where the tablet was off (Scenario 3.1) recorded the lowest scores across anthropomorphism, animacy, and likeabil-

Table 4. Median scores and Wilcoxon test results for GQS dimensions across scenarios (SC) 2.

GQS dimension	Median SC 2.1	Median SC 2.2	Median SC 2.3	Median SC 2.4	SC 2.1 vs 2.2	SC 2.1 vs 2.3	SC 2.1 vs 2.4	SC 2.2 vs 2.3	SC 2.2 vs 2.4	SC 2.3 vs 2.4
Animacy	14	21	20	21	**p<.001**, W=31[a]	**p<.001**, W=159[b]	**p<.001**, W=197[c]	**p=.020**, W=892[d]	**p<.001**, W=1367[e]	**p=.033** W=1077.5[f]
Intelligence	16	20	19	20.5	**p<.001**, W=120[a]	**p<.001**, W=400[b]	**p<.001**, W=381[c]	**p<.001**, W=452.5[d]	**p<.001**, W=683[b]	**p<.001** W=613[f]
Likeability	15	20	18	20	**p<.001**, W=73.5[a]	**p<.001**, W=288[b]	**p<.001**, W=110.5[c]	**p<.001**, W=392[d]	p=.115, W=700.5[e]	**p<.001** W=321.5[f]

[a] H1: SC 2.1 < SC 2.2, [b] H1: SC 2.1 < SC 2.3, [c] H1: SC 2.1 < SC 2.4,
[d] H1: SC 2.3 < SC 2.2, [e] H1: SC 2.2 < SC 2.4, [f] H1: SC 2.3 < SC 2.4.

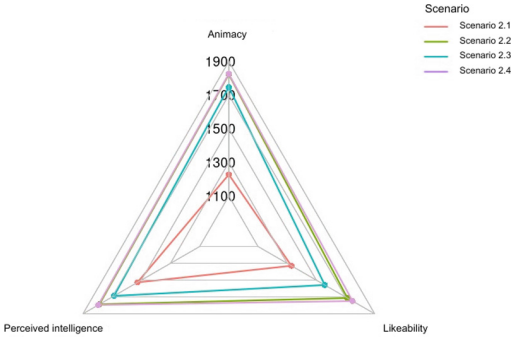

Fig. 3. Comparison of Animacy, Perceived Intelligence, and Likeability characteristics in Scenario 2. The graph is based on the sum of the Likert scale scores for each component of the scenario.

Table 5. Median scores and Wilcoxon test results for GQS dimensions across scenarios (SC) 3.

GQS dimension	Median			SC 3.1 vs 3.2	SC 3.1 vs 3.3	SC 3.1 vs 3.3
	SC 3.1	SC 3.2	SC 3.3			
Anthropomorphism	8	11	15	$\mathbf{p < .001}$, $W = 227.5^a$	$\mathbf{p < .001}$, $W = 46.5^b$	$\mathbf{p < .001}$, $W = 158.5^c$
Animacy	9	11	16	$\mathbf{p < .001}$, $W = 388^a$	$\mathbf{p < .001}$, $W = 62^b$	$\mathbf{p < .001}$, $W = 66.5^c$
Likeability	13	15	18.5	$\mathbf{p < .001}$, $W = 199.5^a$	$\mathbf{p < .001}$, $W = 68^b$	$\mathbf{p < .001}$, $W = 53^c$

[a] H1: SC 3.1 < SC 3.2, [b] H1: SC 3.1 < SC 3.3,
[c] H1: SC 3.2 < SC 3.3

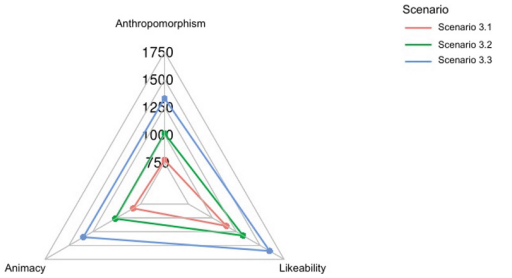

Fig. 4. Comparison of Anthropomorphism, Animacy, and Likeability characteristics in Scenario 3. The graph is based on the sum of the Likert scale scores for each component of the scenario.

ity. In contrast, Scenario 3.3, which incorporated dynamic facial expressions, excelled in all these dimensions, with likeability being particularly prominent.

The results of the Wilcoxon rank sum tests indicate statistically significant differences ($p < 0.001$) in each of the measured characteristics when comparing Scenario 3.1 to Scenarios 3.2 and 3.3, highlighting its notably reduced perceptions across anthropomorphism, animacy, and likeability (Table 5).

Scenario 3.2, featuring static facial expressions, achieved similar scores for anthropomorphism and animacy, yet still fell short compared to Scenario 3.3, which demonstrated significant advantages in these dimensions as well ($p < 0.001$). These findings underscore the importance of integrating interpersonal dynamics, such as facial expressiveness, alongside functional aspects in designing socially interactive technologies.

The findings are visually represented in Fig. 4, which provides a comparison of anthropomorphism, animacy, and likeability characteristics across the different scenarios, utilizing the sum of the Likert scale scores.

5 Conclusions

This study examined the factors influencing trust in human-robot interactions (HRI), focusing on the robot as a social actor expected to meet social norms and behave appropriately within its environment. Trust was defined as the ability to perform tasks effectively, with key dimensions including familiarity, comprehensibility, and robustness, underscoring the importance of communication and perceived intelligence.

The descriptive analysis revealed a well-balanced participant demographic in terms of gender, age, and occupation. While age, being in the technology field, and ownership of robotic equipment at home did not show significant correlations with trust dimensions, weak correlations with gender emerged, with males tending to rate some trust-related dimensions slightly lower. While suggestive, these findings do not indicate a strong or consistent influence of gender on trust. These results are consistent with previous research indicating that females reported higher levels of trust and perceived trustworthiness in an autonomous security robot compared to males [10]. However, the weak nature of the correlation indicates that other factors may also significantly shape trust perceptions. Thus, while gender may contribute to a nuanced understanding of trust, these findings should be interpreted with caution, and further research is essential to explore the complexity of these relationships more comprehensively.

1. **Error responses:** The scenario in which the robot explained its error and subsequently apologized received the highest ratings for likeability and perceived intelligence. This supports **RH1**, demonstrating that apologies improve the perceived likeability of the robot. Providing a justification for an error followed by an apology further improves perceived likeability, while a simple apology is rated higher than only justifying the error. However, justification improves perceptions of intelligence, confirming **RH2**. The lack of explanations correlates with lower perceived intelligence assessments, aligning with **RH3**.

2. **Verbal interactions:** The highest ratings for animacy, likeability, and perceived intelligence occurred when the robot sought permission before proceeding with tasks and executed tasks only upon user request. This scenario validates **RH4**, indicating that lack of communication can diminish user trust in the robot. Actively engaging with users prior to action, as noted in this scenario, supports **RH5** and suggests that the robot is viewed as having greater animacy, likeability, and intelligent when it interacts with users beforehand. Moreover, establishing communication improves the perceived intelligence and likeability, supporting **RH7**.
3. **Facial expressions:** The use of dynamic facial expressions on the robot resulted in higher ratings for anthropomorphism, animacy, and likeability. This outcome validates **RH8**, as the absence of facial expressions reduces perceptions of anthropomorphism, animacy, and likeability. It was also observed that displaying a face on the tablet, even without eye movement, improves perceptions of anthropomorphism, corresponding with **RH9**. Specifically, eye movement positively influences the perceptions of anthropomorphism, animacy and likeability, thus confirming **RH10**.

This study contributes to the understanding of trust in human-robot interactions; however, it has limitations that must be acknowledged. While the sample size was balanced, it may not fully represent diverse demographics, which could limit the generalizability of the findings. Furthermore, the scenarios tested were limited in scope, and reliance on self-reported measures may introduce bias in trust assessments. Future research should build on this study by utilizing larger and more diverse samples to enhance the validity of the findings. Given the low reliability (Cronbach's alpha value of 0.192) observed with the Big Five Inventory (BFI) questionnaire, which restricted our ability to assess personality traits, future studies should consider alternative measurement tools to more accurately capture this dimension. Additionally, exploring a wider range of interactive contexts and incorporating longitudinal designs could provide deeper insights into how trust develops over time in human-robot interactions.

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