Unveiling Trust Dynamics with a Mobile Service Robot: Exploring Various Interaction Styles for an Agricultural Task

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***Abstract*—As robotics, particularly in agriculture, become more prevalent, understanding the role that different factors play on the trust levels that users have in these robots becomes crucial to facilitate their adoption and integration into the industry. In this paper we present the results of a within-subjects study that included between-subject factors exploring how prior experience with robotics and different interaction styles with a mobile manipulator robot may affect trust levels in said robot before and after the completion of an agriculture-related manipulation task. The results show that interacting with the robot helps improve trust levels, particularly for those without prior experience with robotics, who present a higher trust improvement score, and that an interaction style involving physical human-robot interaction (pHRI), more specifically Learning by Demonstration, was favoured versus less direct interaction styles. We found that incorporating Text-to-Speech (TTS) can be a good design choice when trying to improve trust, and that the improvement score for trust before and after interaction with the robot was significantly higher for older age groups, with these participants being more conservative with their reported trust level before the interaction. Overall, these results offer insights into different interaction styles and their effect on trust levels for an agriculture-related manipulation task, and open the door to future work exploring further interaction styles and task variations.**

***Index Terms*—human-robot interaction, trust, interaction styles, agriculture**

I. Introduction

In recent years, as the sophistication of robotics solutions has increased, more and more sectors, especially agriculture, have turned to robotics to help improve and solve today's global problems. The world is expanding at breakneck speed, and current United Nations (UN) predictions suggest that the human population could increase by 2.15 billion people from today's recorded levels, reaching 9.15 billion by the year 2050 [1]. To feed such a large population, agricultural production must rise dramatically [21], [6], and by utilising these robotic solutions can effectively boost crop yields while increasing efficiency and bolstering sustainability [13]. Agriculture has opened its doors to innovation as a result of the surge in the artificial intelligence sector, growing population, and the creation of more utilitarian robots. According to Verified Market Research, the agricultural robots industry is projected to reach \$11.58 billion by 2025 [22], making this one of the most investable industries in the coming century. Although the agricultural sector is calling for these robotics solutions, more research must be conducted before these robots can be implemented within the industry. An important consideration that must be addressed is whether or not people can, or are willing to, trust these robots when they are integrated within the industry.

One thing is to be able to develop robotics solutions for agricultural problems, but if people are unwilling to put their trust in these new robots, their integration into industry will be halted. As the advantages, automation, history, and future have been identified [14], they also state that the "trust in the robotic equipment is not quite built completely", highlighting that there are concerns about implementing these robotic solutions into industry. The agriculture sector is primarily seen as an older individuals' profession, as indicated by Guo, G. et al. [11] in their study, in which they aimed to identify the impact of an ageing agricultural labor population, with these people who have been working in the same way, day in and day out for the past several decades, a correlation between the acceptance of these solutions into farms and the farmer's age could be seen as they are set in their ways. This is supported by the study conducted by Das, V. J. et al. [4] on the integration of technology within Irish farms. Through their research, they identified that people with lower levels of education and who were older were less likely to integrate these new robotic solutions into their farms, even though evidence proves better results. This emphasizes the importance of trust within these robots and the need for more research into the factors that influence the level of trust people bestow on them.

In this paper, we present a study that provides insight into the impact on trust of different styles of interaction with a mobile manipulator robot whilst completing an agriculture-related manipulation task using the robot TIAGo [1].Trust is a complex multifaceted concept that can be affected by a number of internal and external factors such as cultural background, prior experience with technology/ robots. During the study, we utilised a within-subjects design that included two between-subjects factors. Because of the complexity of trust and of measuring it, we decided to use, along with self-reported trust, tools such as the Negative Attitude towards Robots Scale (NARS) Questionnaire [20] and Godspeed Questionnaire [2],as well as semi-structured interviews with

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a sample of the participants. This enabled us to delve into subjective measures of trust. While NARS aims to measure a range of negative feelings and responses towards robots, Godspeed Questionnaire assesses perceived anthropomorphism, animation, likeability, intelligence, and safety of robots. The standard version of the NARS questionnaire can be seen in table I. The use of these methods contributes to a deeper understanding of trust dynamics in HRI. Within this study, aspect from both where utilised to gauge the participants initial attitudes towards robots in general before further exploration was conducted through questionnaires/interviews.

TABLE I: NARS questionnaire as defined by Nomura et al. [20]

Item no.	Questionnaire item	Subscale
1	I would feel uneasy if robots really had emotions.	S2
2	Something bad might happen if robots developed into living beings.	S2
3	I would feel relaxed talking with robots (Reversed item).	S3
4	I would feel uneasy if I was given a job where I had to use robots.	S1
5	If robots had emotions, I would be able to make friends with them (Reversed item).	S3
6	I feel comforted being with robots that have emotions (Reversed item).	S3
7	The word “robot” means nothing to me.	S1
8	I would feel nervous operating a robot in front of other people.	S1
9	I would hate the idea that robots or artificial intelligences were making judgements about things.	S1
10	I would feel very nervous just standing in front of a robot.	S1
11	I feel that if I depend on robots too much, something bad might happen.	S2
12	I would feel paranoid talking with a robot.	S1
13	I am concerned that robots would be a bad influence on children.	S2
14	I feel that in the future society will be dominated by robots.	S2

Our study aims to answer the following research questions:

RQ1 How does having prior experience using robotic solutions affect trust levels before and after interacting with TIAGo?

RQ2 How do different types of interaction with TIAGo during a manipulation task affect trust levels before and after the task?

From these research questions, we worked with the following hypotheses:

H1 The level of trust the user has in the robot will increase after interacting with it;

H2 Interactions involving a higher level of interaction will yield higher levels of trust.

A. *Note on terminology*

In this paper, the term “HRI robot” is utilized to underscore the significance of the overall interaction between robots and humans, rather than focusing solely on the type of robot involved (e.g., co-bot, social robot) or the nature of the interaction (e.g., instruction-based, social interaction-based), when we refer to HRI robots in this paper, we refer to any type of robot a person/s may need to interact or engage directly with during the task in hand.

II. Related Work

A. *The Challenges of HRI Robots Building Trust*

Trust is a critical aspect of HRI that started receiving increasing attention in research in recent years, despite a reported lack of focus on this aspect until approximately 2008 [15]. Various methods, including subjective and behavioral measures, have been employed to gauge trust levels in this area. With robotics solutions increasingly prevalent across industries, particularly in agriculture, trust in these systems becomes paramount to enable their adoption and integration, with adoption referring to the stage in which they are initially selected for use, and integration referring to a sense of acceptance and transparency within the user environment once they’ve been adopted [7]. Groom and Nass [10], emphasize the importance of trust in team dynamics, crucial for effective operation, with Hancock et al. [12] highlighting how trust influences humans’ reliance on robotics systems, particularly in challenging environments. Yet, as De Visser et al. [5] caution, insufficient trust may prompt user intervention when this is not necessary, while Malle [17] warns against excessive trust leading to unrealistic expectations, something that could lead potential safety issues in safety-critical scenarios.

Desai et al. [19] suggest differences in trust development between human-robot and traditional automated system interactions.While trust in traditional automated systems relies heavily on reliability and predictability over time, trust between human-robots involves a complex interplay of technical, social, and emotional factors. In HRI, factors such as anthropomorphism, communication style, transparency, and perceived intentions play crucial roles in shaping trust. Additionally, the physical embodiment of robots introduces unique dimensions to trust development, as humans may attribute human-like qualities to robots based on appearance and behavior. Understanding these differences is vital for designing and deploying robots that can effectively earn and maintain human trust in various contexts. Yagoda and Gillan [30] argue that trust evaluation often overlooks key robot attributes.

Stergiou, A. and Poppe, R. [28] suggest that while most metrics of trust between people are based on moral principles like honesty and loyalty, the majority of HRI trust metrics rely on the user’s belief that the robot can complete a task successfully. However, according to Coeckelbergh [3], there are more variables to consider when determining whether a robot is judged trustworthy in HRI than merely whether the robot can execute a predetermined task effectively or not. He created two main categories for these variables, “contractarian-individualist” and “phenomenological-social”. The former claims that an interaction between a human agent and an artificial agent highlights the differences between the two agents, while the latter suggests that it is more complex and that the robots should be seen as multi-stable as they are much more than machines, treating them more like one would an animal or another human. Further delving into the complexity of trust in HRI robots, Galvez Trigo et al. [9] also highlight that other factors to consider are the trust in manufacturers or institutions deploying or supplying the robot to be used, as well as general knowledge about the robot's capabilities. This highlights how challenging it is to build and measure trust towards HRI robots.

Steinfeld, A., et al. [27] report on the challenges in accurately measuring trust, discussing difficulties in determining trust levels in ecologically flawed environments. Flook, R. et al. [8] found limitations in relying solely on post-hoc questionnaires to understand trust dynamics, emphasizing the need for continuous assessment. Whereas, although they are indirect measures of trust, Flook, R. et al, [8] found that behavior-based objective measurements could be less susceptible to post-hoc "reconstruction and rationalisation".

Regarding trust measurement in HRI, Yagoda, R.E. and Gillan, D.J. [30] argue that trust has primarily been evaluated in the context of automation, and caution against its indiscriminate application in HRI in general. While automation is a key aspect of HRI, it underscores the necessity for a more refined trust metric specific to HRI.

B. How HRI Robots Interact with the User

The degree of trust that may be placed on a robot critically depends on how humans engage and communicate with it. According to Hancock, P.A. et al. [12], trust is a relational concept that requires the presence of at least three elements: a human information transmitter, a robot information receiver, and a communication channel connecting the two, being the interaction.

The issue of whether communication styles and cultural differences affect people's willingness to accept robot-generated recommendations is one that Rau, P.P., et al. [25] raise. A small sample of Chinese and German students were approached in this study to record their tolerance and acceptance of a robot that communicates in both their native tongue and English. They confirmed that when a robot spoke in the participants' native language, they seemed to favor an implicit communication style and the decisions made by the robot. Participants also thought the robot was more "likeable, trustworthy, and credible" than when the robot spoke in English. An assumption that can be drawn from this study's findings is that people are more likely to trust a robot if they find it to be likeable. Vlachos, P.A., et al. [29] suggests that likability is an emotional bond between two people that can be described as affectionate, a feeling that is much more greatly accepted. This suggests that, when designing a robot that will interact with humans, likability —which is a critical component in assessing trustworthiness— should be taken into account.

Trust is at the heart of people's desire to recognize and utilize a non-human agent, hence its importance in the adoption and integration of HRI robots. The terminology "Theory of Mind" (ToM), which was first used by American psychologists Premack, D. and Woodruff, G. [23], refers to the capacity to comprehend the ideas and intentions of others that are different from one's own. Since people's capacity to trust another agent depends on our own interpretation of that entity's behavior, according to Rabinowitz et al. [24], it is possible to draw a connection between trust and ToM as interconnected and interdependent notions within HRI. In order to determine whether there is any relationship, participants in the study by Mou et al. [18] played a "Price Game" with the same robot while varying their ToM to see if there was any correlation between the two. Their findings support the idea that humans are more likely to change their opinions about a product's price after hearing a robot with a high ToM level recommend it. This suggests that robots with higher levels of ToM are perceived as being more trustworthy than those with lower levels. Little is known about how different styles of interacting with a robot, with some involving more close interaction than others, whilst performing the same task, may affect the likeability or trust in the robot being used.

III. Methodology

The study presented in this paper utilises a mixed-methods, within-subjects design (Within factor 1: pre/post questionnaire; Within factor 2: three interaction types: fully programmed, controller, Learning by Demonstration), and two between-subjects factors (Between factor 1: experience of interaction with robots; Between factor 2: age group). The participants were asked to complete an agriculture-related manipulation task using the mobile manipulator robot TIAGo, consisting of picking a piece of fruit and moving it to a different location. Besides completing the task, participants were asked to complete an initial questionnaire comprising demographic data (i.e., gender, age group, prior experience with robotics), the NARS questionnaire, and the Godspeed questionnaire, both NARS and Godspeed administered before and after interacting with the robot. Approval for this study was obtained from the University of Lincoln Ethics Committee (Ref.: UoL2022_9540), and we adhered to the risk management procedures established for working with TIAGo in the robotics labs of the School of Computer Science of the same university.

A. The task set-up, software and hardware used

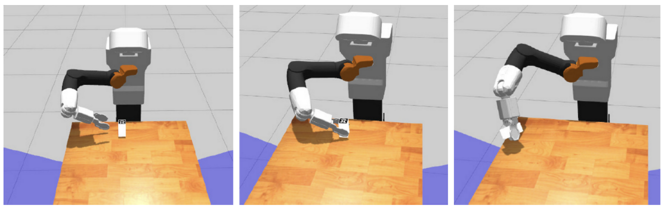
The study involved asking the participants to use TIAGo to move a piece of fruit from point A, on one table, to point B, on a different table, using three different interaction styles.

The use of a hardware-agnostic controller, written as Robot Operating System (ROS) Control plugins, was chosen due to its effectiveness in providing participants with full control over the robot and simplifying the development of high-level applications by abstracting the complexity of the robot.

The "Moveit!"[2] tutorial repositories were utilized to program the task. Before the repository could be utilized on the physical robot, we established the graphical user interface (GUI) in simulation; this allowed for a better understanding of the movement of the joints and how they were going to move when completing the task of moving the fruit from point A to point B, which was from one table to another. Within the "Moveit!" repository, there are multiple different methods that could have been used. The foundation of this

[2] http://wiki.ros.org/Robots/TIAGo/Tutorials/MoveIt/Pick_place

study utilized the “Pick and Place demo” and “Planning in Cartesian Space”. The “Pick and Place demo”, which can be seen in figure 1 aided with the understanding of identifying, grasping, and moving an object. However, this did use a QR code to locate the object that it was trying to use. Hence, planning in the Cartesian space was later explored to use the specific coordinates of the object in simulation to be able to identify it.



(a) Identify (b) Grasp (c) Move

Fig. 1: Pick and Place Demo

We also used the Learning by Demonstration repository[3] for an interaction style based on Learning by Demonstration. Initially, the creation, population, and compilation of the catkin workspace were required. Subsequently, the GUI was executed. Concurrently, gravity compensation for the entire arm repository was enabled in a separate terminal. Following this, we designated which joint TIAGo would record during the demonstration. For this study, only the arm joints and grippers were necessary, as the head and torso remained stationary. Following joint selection, we could commence the recording process via two methods: Continuous, or Waypoints recording. While similar, continuous recording facilitates a smoother replication compared to Waypoints recording, which mandates hitting specific points within the demonstration, resulting in a more rigid interaction. Finally, options for stopping, saving, and adjusting playback speed were available. The demonstration could be played back at half the speed, the original speed, or twice the speed. This study utilized continuous recording with playback at the original speed, a deliberate choice aimed at fostering a more human-like interaction devoid of robotic movements at variable speeds.

During the study, we also used the joystick controller that came with TIAGo. Initially, the controller was configured to facilitate the movement of TIAGo’s torso. Therefore, prior to participants’ engagement, adjustments were made to the controller’s functionalities. Specifically, the controller’s functions were modified to enable the manipulation of TIAGo’s arm via joysticks, thereby providing the necessary degrees of freedom for arm movement and end effector control for object manipulation. This adjustment mitigated user risk by restricting robot movement while still allowing users to manipulate the arm, facilitating object grasping and movement to its designated location.

[3]https://github.com/pal-robotics/learning_gui

B. Design

This study investigated the pre- and post-interaction levels of trust individuals exhibit toward HRI robots, together with the potential influence of three different interaction styles. The study had 3 stages: pre-interaction questionnaires (demographics, NARS and Godspeed), task completion using the three different interaction styles, and post-interaction questionnaires (NARS and Godspeed). The three interaction styles can be seen in figure 2 and were as follows.

1) Fully programmed - Low interaction level: The researcher programmed the robot to complete the task following the participant’s instructions whilst the participant observed, with this involving minimal interaction with the robot.

Having TIAGo complete the task with a low level of interaction (without any physical assistance from the participants) allowed us to later compare with higher levels of interaction, and it reflects an interaction style that often happens in environments shared between humans and robots whilst these are completing a task.

2) Learning by Demonstration - Medium interaction level: During this interaction style, the participant instructed the robot’s arm movements through kinesthetic teaching for it to complete the task, using the Learning by Demonstration repository described in the previous section.

Whilst this style require more interaction between the participant and the robot, as they were not controlling the physical robot in real time, this interaction style was chosen as the medium interaction level style for our study as it allows participants to interact with TIAGo swiftly and easily by pre-recording movements and having the robot repeat them for the task.

3) Controller - High interaction level: For this interaction style, the participant had to use the joystick controller that came with TIAGo to control the movements of the robot in real time. This provided a higher level of interaction between the robot and the participant, and was chosen as the high interaction level style for our study.

(a) Controller (b) Programmed (c) Demonstration

Fig. 2: Different interaction styles used during the study

It may be noted that we decided not to use voice commands through speech recognition to perform the task. This was because the conditions in which a real-life interaction with TIAGo would happen during a task of this nature, would not easily allow for this type of interaction due to environmental factors such as noise levels, the presence of other people, and the distance between the robot and its operator. Nonetheless, and although the main focus of the study was on the different interaction styles and their effect on trust, we decided to incorporate the use of the text-to-speech (TTS) feature of TIAGo with one third of the participants to explore whether those that interacted with TIAGo with TTS on reported a higher level of trust post-interaction than those that didn't. We used this while the selected participants were interacting with the robot as to attempt a more natural interaction by greeting the participants and using conformation statements such as "I understand" and "thank you".

C. Participants

We recruited a total of 30 participants from different age groups, all aged over 18 (9 female, 21 male). For the purposes of the study, two groups were established, each comprising 15 participants. One group was comprised of individuals possessing expertise in robotics, mainly encompassing professionals such as colleagues, students or university lecturers. Conversely, the second group was comprised of members of the general public with no prior experience or knowledge in robotics. Aside from geographical proximity to be able to participate in the study in person and being over 18, no additional external eligibility criteria was imposed during the participant recruitment phase. Each participant got to experience all three styles of interaction throughout the study.

D. Procedure

After obtaining ethical approval, a call for participation was made public. Those interested in participating in the study contacted the research team and were invited to come to the Isaac Newton Building on the Brayford campus of the University of Lincoln, where they met the researcher running the study and were escorted to the designated laboratory where the study was conducted under controlled conditions. Upon arrival, participants were invited to ask questions and informed written consent was obtained. Participants commenced their participation in the study by completing the designed preliminary questionnaire which included the NARS & Godspeed questionnaires while also capturing demographics (age, gender, prior experience with robots). Then, they proceeded to perform the task with the robot in the experimental room, under the guidance of the researcher.

During the experiment, each participant interacted with TIAGo under the three interaction styles described. To mitigate any ordinal bias, the sequence of interactions was systematically varied for each participant. Nevertheless, the fundamental structure of the experiment remained consistent: participants were introduced, informed of the type of interaction they would undergo, engaged in said interaction, sequentially experienced the remaining two interaction styles, and subsequently completed the post-interaction questionnaires (NARS and Godspeed).

The assigned task remained the same throughout each interaction where the goal was to have the robot identify the object (plastic apple), grasp it and then move it to a secondary location on the table. The level of control varied from one condition to the next.

Additionally, TTS features were used on one third of the participants as the importance of verbal communication has been highlighted throughout other studies in HRI [25]. Those participants that interacted with the robot with TTS enabled were additionally monitored to observe their reactions when TIAGo started to speak with them.

Once the participants had completed their questionnaires and interactions they were invited to participate in a short semi-structured interview to clarify and contextualise their responses.

IV. Results

In this section, we present the quantitative results of our study. Data was analysed using IBM SPSS Statistics, and the responses obtained during the short semi-structured interview at the end of the study were used to corroborate and contextualise results.

A. Trust Level Before & After Interaction

A paired sample t-test was conducted to assess whether there was a statistically significant difference in the level of trust participants had in TIAGo to complete the task before interacting with it compared to after interacting with it, which results can be seen in figure 3. With t(29) = -11.771 and p ¡ 0.0005, indicating a statistically significant difference, results suggest that there was a statistically significant increase in trust levels following the interaction, from (5.13 ± 1.943) to (7.70 ± 1.705), p ¡ 0.0005; an improvement of (2.567 ± 1.194). This indicates that interacting with TIAGo significantly increased the participants' trust score within this sample group. While the paired t-test indicates whether differences between group means are "real" (i.e., different in the population), it does not quantify the "size" of that difference.

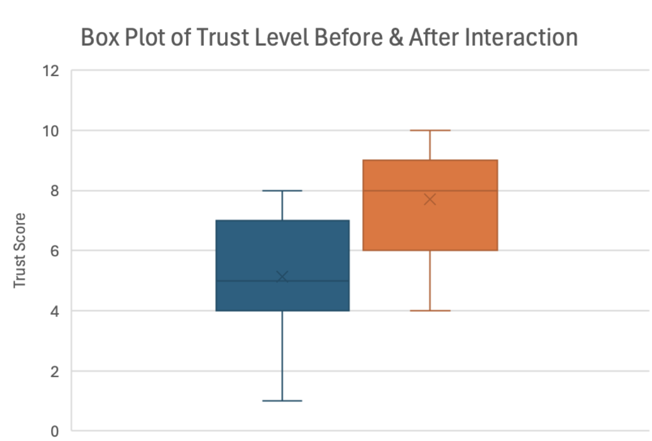


Fig. 3: Mean Trust Level Before & After Interaction Box Plot

B. Improvement Score Between Groups

We found that participants with no experience in robotics had a statistically significantly higher mean trust level (3.00 ± 1.134) after interacting with TIAGo compared to the participants with experience in robotics (2.13 ± 1.125). This could be due to the initial trust levels being different between the groups; the 15 participants with prior experience averaged a starting trust score of 6.6, whereas the group with no experience averaged a starting trust score of 3.6. A line graph was created (seen in figure 4), illustrating the rate at which the trust levels of each group not only increased but initially differed. The experienced group showed greater trust in TIAGo to complete the task, despite lacking interaction. Error bars on the graph indicate the Standard Deviation for both the non-experienced (1.121 & 1.549) and experienced group (1.234 & 1.014) before and after. The data suggests that non-experienced participants, while initially skeptical due to lack of robotics experience, grew more comfortable trusting TIAGo after interaction.

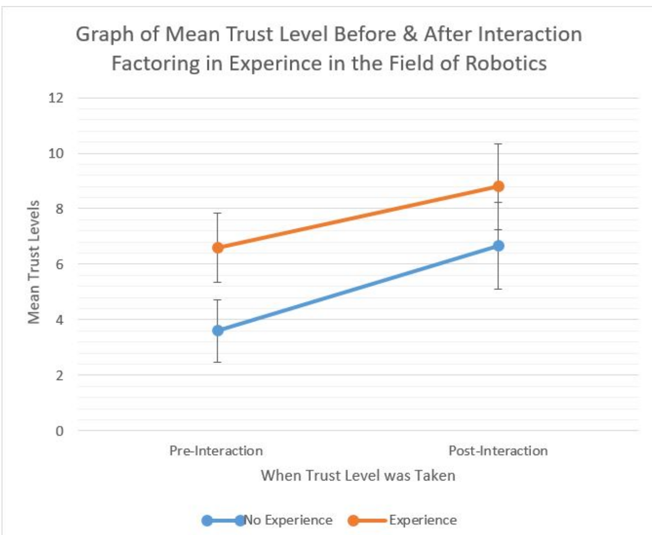


Fig. 4: Line Graph Showing the Mean Trust Level of both Experienced and Non Experience in Robotics Groups Before & After Interaction

C. Which Interaction Was Trusted Most by Participants

Having identified that interacting with TIAGo had an overall effect on trust levels, each interaction the participants had with the robot was explored in depth to be able to identify if there was a particular interaction style that participants found more trustworthy than others. A Chi-Square test was used to determine which of the three interactions each participant stated they trusted the most. From this test, it was identified that Learning by Demonstration was reported to be the interaction almost every participant stated to trust the most out of the interactions (24 out of the 30 participants). These statistics suggest a clear variation in trust between the three different interactions. As a result, a chi-square test of association was conducted, which revealed a statistically significant association between the types of interaction and trust.

$$X^2(2) = 29.600, \quad p < .000 \tag{1}$$

D. Effect of TTS Features

While there were only three different types of interactions that every participant experienced throughout the experiment, one-third of both sample groups experienced interactions with the Text-to-Speech (TTS) function active on the TIAGo robot. This was to monitor whether verbal communication between the robot and the participant would affect how much the participant would perceive trusting TIAGo. We found that the participants who experienced the TTS function during interactions had a statistically significantly higher improvement score (3.00 ± 1.700) when it came to trusting TIAGo at the end of the experiment compared to the participants that did not experience the TTS function (2.35 ± 0.813), t(28) = -1.440, p ¡ 0.0005, regardless of whether they had prior experience with robotics or not. The majority of participants responded to TIAGo with basic greetings such as "Hello", even though they were not under the impression that the robot could understand what they were saying. However, there was one case in the group that had no experience in robotics where the participant not only greeted TIAGo back but also said "Hi TIAGo, my name is ...". They unconsciously became more comfortable around TIAGo by moving closer to the robot and scored one of the highest improvement scores.

E. Age Factor

The effect of demographic factors was tested to see if there were any correlations between the ages of the participants and which interaction they trusted more. A Cross-Tabulation Chi-Square test was used to determine this due to the data being categorized by more than one variable. Participants were split into four different categories: 18-24 (10 participants), 25-34 (7 participants), 35-44 (9 participants), and 45-54 (4 participants) totalling 30 participants. Although there was no statistical significance between the age groups and the type of interaction they trusted most,

$$X^2(2) = 2.002, \quad p < .367 \tag{2}$$

an additional One-Way ANOVA was used to determine whether the age of the participant had an effect on their overall improvement score of trust. A statistically significant difference between groups was observed as determined by the one-way ANOVA (F(3,26) = 3.882, p = .020). A post hoc test revealed that the improvement score was significantly lower in younger participants aged 18-24 (2.5) compared to older participants aged 45-54 (5.25), with a statistically significant difference of (p = 0.025). There was no statistically significant difference between the 25-34 and 35-44 groups. The graph in figure 5 visually represents the trend of the improvement score through the different age groups. This is indicative that the improvement score increases the older the participant sample is.

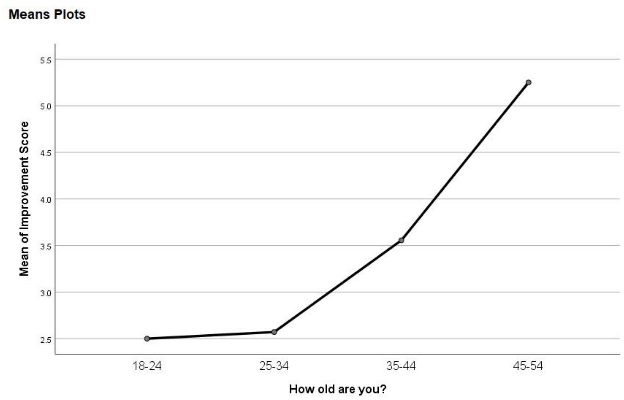


Fig. 5: Mean Improvement Score vs Age Groups

V. Conclusions

The aims of this study were to explore how having prior experience with robots can affect trust levels before and after interacting with TIAGo (RQ1), and how different interaction styles can also affect these trust levels (RQ2). Further to this, we started the study with two hypotheses:

H1 The level of trust the user has in the robot will increase after interacting with it;

H2 Interactions involving a higher level of interaction will yield higher levels of trust.

Regarding RQ1, an interesting finding that emerged from our study is the difference between the two sample groups in trust levels before and after interacting with TIAGo. The group with previous experience in robotics trusted the robot significantly more before and after any interaction, with an average trust score of 6.67 before and 8.80 after. In comparison, the group without prior experience was more hesitant in trusting TIAGo before interacting, with an average trust score of 3.60, but showed a larger improvement score than the other group, with an average trust score after interaction of 6.60. This suggests that, despite initial hesitation, for people with no prior experience in robotics, being able to interact with the robot helped them significantly improve their trust level, and that, regardless of a person's previous experience in robotics, interacting with the robot during a specific task does affect trust in said robot for that task, leading to an increase in this, which in turn leads us to accept H1. This notion has been highlighted by Kalinowska, A., et al, [16] where the importance of physical human robot interaction (pHRI) is the next frontier.

Regarding RQ2, our study suggests that people's trust levels toward the robot's behavior do indeed change after interacting with it, as the recorded level of trust had a statistically significant increase. The various types of interactions also contributed to the assigned level of trust, with Learning by Demonstration determined to be the most trusted interaction, as indicated by 24 out of the 30 participants. This leads us to reject H2, as our interaction style with a higher level of interaction was using the controller. However, it is not surprising that this interaction style were preferred over the fully programmed style, as it agrees with existing literature indicating that opting for Learning by Demonstration over alternative robot learning methodologies becomes particularly compelling in scenarios where ideal behavior cannot be readily scripted, as typically done in traditional robot programming, nor clearly defined as an optimization problem, but rather can be effectively demonstrated [26]. It was also interesting to observe that the improvement score on trust levels was significantly higher for those participants the robot communicated with using TTS, which suggests that this may be a desirable feature to include in the design of HRI robots where trust between robotic agent and person is of high importance.

Other major findings non-related directly to our research questions show a statistically significant difference in trust improvement scores between different age groups, with the most significant disparity observed between the younger group (18-24) with an average improvement score of 2.5 and the older group (45-54) with an average improvement score of 5.25. This suggests that, although trust levels seem to calibrate to a similar level after the interaction, older participants had initially a lower level of trust, as opposed to younger ones. However, when testing other demographic factors such as gender, there were no statistically significant differences between male and female participants.

A. *Limitations and Future Work*

Whilst our study has helped us yield more clarity over how different interaction styles with a mobile manipulator robot can affect trust, as well as to obtain a better understanding of the factors than can help us obtain a higher improvement score when it comes to trusting a robot before and after an interaction, there are certain factors that limit the scope of our work.

It should be noted that, depending on the task in hand, other interaction styles different to the ones we explored could be an option and, whilst our findings suggest that a more direct interaction with the robot will lead to a higher trust level during an object manipulation task, we cannot conclude that this will be the case for every interaction style involving close interaction, especially as this can present variations depending on the nature of the task. This, however, presents an opportunity for future work, where other interaction styles could be considered for different tasks, using the conclusions of our work as a starting point.

Something else to consider for future work is exploring how trust can be sustained and maintained, given that a robot might not always perform a task as expected, and whether different interaction styles may or may not have an effect on maintaining/regaining trust in such situations.

Our study was conducted in a controlled lab setting to be able to create a better understanding of how the factors explored affected trust, however, future work may include following similar approaches but with the interaction taking place in a real-life situation. This would allow to consider how other external, situational and environmental factors affect trust levels.

To be able to generalise the findings of the study the inclusion of more than 30 participants would be required with a more even distribution of participants within all age categories.

As with most studies exploring trust in robotic systems, it's important to acknowledge the ongoing challenge of effectively monitoring and measuring, and that there is yet to be a validated optimal way to measure participants' trust levels to allow for a better understanding of how interacting and the styles of interaction may affect the level of trust participants have in a robot whilst completing a task.

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