Enhancing Human-Robot Interaction in Healthcare: A Study on Nonverbal Communication Cues and Trust Dynamics with NAO Robot Caregivers

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***Abstract*—As the population of older adults increases, so will the need for both human and robot care providers. While traditional practices involve hiring human caregivers to serve meals and attend to basic needs, older adults often require continuous companionship and health monitoring. However, hiring human caregivers for this job costs a lot of money. However, using a robot like Nao could be cheaper and still helpful. This study explores the integration of humanoid robots, particularly Nao, in health monitoring and caregiving for older adults. Using a mixed-methods approach with a within-subject factorial design, we investigated the effectiveness of nonverbal communication modalities, including touch, gestures, and LED patterns, in enhancing human-robot interactions. Our results indicate that Nao's touch-based health monitoring was well-received by participants, with positive ratings across various dimensions. LED patterns were perceived as more effective and accurate compared to hand and head gestures. Moreover, longer interactions were associated with higher trust levels and perceived empathy, highlighting the importance of prolonged engagement in fostering trust in human-robot interactions. Despite limitations, our study contributes valuable insights into the potential of humanoid robots to improve health monitoring and caregiving for older adults.**

***Index Terms*—Nao Robot, Human-Robot-Interaction, Elder-care, Touch, Hand Gestures, LED Approach, Non-Verbal Cues, Trust**

I. Introduction

The ageing population is a global phenomenon that presents numerous challenges, particularly in elderly caregiving. According to estimates by the Organisation for Economic Co-operation and Development (OECD), by the middle of the 21st century, over 20% of the world's population will be aged 65 and over [1]. As demographics shift and the number of older adults increases, a growing demand for continuous companionship and health monitoring services is growing [2]. Traditional caregiving practices often involve hiring human caregivers, which can be expensive and may not always effectively meet the needs of older adults. However, with advancements in robotics technology, there is a new avenue for addressing these challenges by integrating humanoid robots, such as Nao, in elderly caregiving [3]. Robots can help extend the time older people can remain active and safe in their preferred environment by assisting them in their homes. However, the acceptance of a robotic caregiver is a complex and adaptable issue.

Human-robot interaction (HRI) has emerged as a rapidly expanding discipline that explores how humans and robots can effectively collaborate and communicate. It's not just about language-based interaction but also includes all aspects relevant to communication among physical beings [4]. It encompasses not only language-based interaction but also non-verbal communication, which plays a vital role in influencing human perception and engagement. Non-verbal behaviors of robots, including body movement, spatial distances, touch, and time, are essential elements in facilitating effective communication and interaction between humans and robots [5]. Body movement serves as a powerful means of communication for robots, allowing them to convey intentions, emotions, and states to human counterparts [6]. By adjusting their posture, gestures, and locomotion, robots can express empathy, attentiveness, and understanding, enhancing interaction quality and fostering trust and engagement. In addition, a robot may use different colours or patterns of LED lights to indicate its various statuses, such as happiness, sadness, and neutral position [7]. However, it is important to recognize that the acceptance of robots is a complex process, and acceptance of robots by older individuals is influenced by various factors, and the ones mentioned are not the only ones to consider

Numerous studies have been done where humanoid robots are used for various disciplinary fields through non-verbal cues in HRI. It is highlighting the crucial roles in enabling effective communication between individuals and robots. Akalin et al. [8] demonstrated the effectiveness of a robot designed for elder care in terms of security and safety. A Pepper robot with nonverbal gestures like arm gestures and head nodding was used. In another study, Nao [9] robots used iconic gestures to support children's language learning. In [9], the authors used the Pepper robot to assist people with dementia in assessing the perceptions of care partners and healthcare workers. Johnson et al. [7] presented various multimodal behavior patterns of Nao robot such as hand movement gestures and eye LEDs patterns and facial expression. Robot-initiated physical contacts, such as handshakes, and hugs, have been demonstrated to enhance trust, motivation, and the perception of a robot's warmth, animacy, and likability in human-robot interactions [10].

The integration of Nao humanoid robots in elderly caregiving holds great promise. These robots offer a unique blend of technology and empathy, with expressive features and graceful movements that enable them to connect with the elderly people effectively. Nao can provide continuous companionship and monitor the health of older adults using special sensors, offering a cost-effective alternative to traditional caregiving practices.

In this study, our research aims using a robot Nao for health monitoring the older people in caregiver or home. To achieve this, we investigate the use of nonverbal communication modalities, specifically unique combination of gestures and LED patterns and touch respectively. In this simulation, we decided to focalize our attention on older adults' attitudes and trust for robots when Nao touches them. By doing so, we can design the robot capabilities of serving the needs of the elderly to improve the quality of life for older adults and address the challenges associated with traditional caregiving methods.

The structure of this article is summarised as follows: In Section II, we provide a comprehensive review of existing literature and related topics. Section III identifies the literature gap and presents our research questions. Section IV details our experimental methodology, describing how we conducted our experiment to address the research questions. Section V contains the presentation of preliminary results, accompanied by relevant statistical analyses if applicable. The discussion of our findings and the acknowledgement of study limitations are covered in Section VI. Finally, in Section VII, we propose possible extensions of the current study.

II. Related Works

The primary objective of socially assistive robots in elderly care is to offer social interaction and monitor health conditions [11]. Researchers have explored various applications of humanoid robots, such as Nao, in providing companionship and healthcare monitoring for older adults. Nonverbal communication plays a crucial role in human interactions, conveying social and emotional information. In the context of HRI, researchers have focused on various modalities such as gestures, facial expressions, posture, gaze, and touch. As robots become more prevalent in healthcare, education, and entertainment, optimizing nonverbal communication in HRI is essential for effective and acceptable interactions [5].

Mazursky et al. [12] demonstrated the impact of robot-initiated touch in healthcare settings, focusing on how different factors influence patient experience. The study involved a robot caregiver performing tasks and providing comfort through touch to understand how people react to such interactions. The researchers conducted a crowdsourced study involving 163 participants, examining the effects of the robot's touch (whether it was present or absent), its intent (either instrumental or affective), its appearance (either resembling a human-like Nao or a more machine-like Stretch), and its tone (either empathetic or severe). The study design involved a mixed-methods approach with touch, robot appearance, and robot tone as variables between subjects and robot intent as a variable within subjects. The findings revealed that participants preferred instrumental (task-oriented) over affective (comfort-oriented) touch. Participants were more comfortable interacting with the human-like Nao than the machine-like Stretch and preferred a consistent robot tone and appearance.

In another study, Johnson et al. [7] investigated the entertainment value of playing games with a humanoid robot Nao, specifically focusing on the game Mastermind. The study focuses on the impact of multimodal behavioral patterns, which are unique combinations of gestures, eye LED patterns, and speech, on the perceived entertainment value. These patterns are designed to imitate four basic emotions (neutral, happy, angry, sad) in combination with five levels of surprise and five levels of confidence. The experiment was conducted using a 3-by-1 repeated-measures design, where the robot's behavioral patterns were manipulated in different ways across three consecutive measurement blocks. Results indicated that the robot's behaviors significantly impacted the entertainment value perceived by the participants, with patterns tied to game progress yielding the highest entertainment value. The study contributes valuable insights into designing robotic interactions for entertainment purposes in healthcare settings.

Akalin et al. [8] conducted a study demonstrating the effectiveness of a Pepper robot equipped with non-verbal gestures for elder care. The robot's arm gestures and head nodding were utilized to enhance security and safety aspects in caregiving environments. This study highlighted the potential of humanoid robots to address the needs of older adults through non-verbal communication cues. Gasteiger et al. [13] conducted a study on elderly individuals who had the robot Bomy in their homes for a week and reported positive experiences and perceptions. The findings indicated that participants accepted Bomy as a valuable daily care assistant, considering it a companion. This suggests promising potential for daily care robots, including Bomy, to assist the elderly, particularly in tasks such as medication reminders and health monitoring.

Webots, a simulation software, proves to be a valuable tool in robotics research and education. It enables researchers to virtualize and experiment with their designs before implementing them in real-world scenarios. This capability helps in reducing costs, enhancing safety, and expediting development [14]. One study utilized Webots to create a virtual apartment where a robot was designed for home care. The findings revealed that the robot was able to successfully navigate and complete its tasks within this simulated environment [15]. This underscores the potential of simulation software as a tool for testing and refining robotic designs before they are deployed in real-world scenarios. Furthermore, Webots has been instrumental in various research works aimed at improving the development and evaluation of autonomous robots.

The existing literature on robotic caregivers, such as Nao, has primarily focused on their appearance and tone, and how these factors influence trust and compliance. Studies have found that the presence of touch from the robot can increase perceived warmth and competence, and reduce discomfort. However, there is a noticeable gap in the literature regarding the specific application of these findings to the design and implementation of robotic caregivers like Nao in real-world settings. Further research is needed to understand how these factors can be effectively incorporated into the design of robotic caregivers to improve patient comfort and the perceived quality of medical care. Based on these results, we propose design guidelines to enhance patient comfort and improve the perceived quality of medical care provided by robotic caregivers capable of social cues.

Fig. 1. Webot simulation of old age home or apartment with Nao robot as caregiver for monitoring the health condition of elderly people.

III. Research Questions

The preceding section highlights the remarkable amount of effort in investigating the presence of touch from the robot, which increases perceived warmth and competence and reduces discomfort. However, there needs to be more literature regarding the specific application of these findings to the design and implementation of robotic caregivers like Nao in real-world settings. Further research is required in order to understand how these factors can be effectively incorporated into the design of robotic caregivers to improve patient comfort, trust, and the perceived quality of medical care [16]. In this article, we will investigate the various nonverbal communication between an Nao robot and older adults in an old age home or their own home setting (Fig. 1). We will utilise various nonverbal communication cues: gestures [17], LED patterns [7], and touch [18]. Both hand gestures and LED patterns are nonverbal cues that can be used to present various positive and negative vibes or meanings. Touch is a nonverbal cue often involved in close interactions among people, such as between caregivers and patients.

Therefore, we have formulated the following question to understand how robotic caregivers like Nao can be effectively integrated into healthcare settings to enhance patient comfort and improve the perceived quality of medical care:

- **RQ1: How the participants perceive when robot Nao touches to observe and monitor the participant's health?**
We will conduct user studies involving participants interacting with the Nao robot in a healthcare setting in a Webot simulation. The participants will experience instances where the robot utilizes touch as a means to observe and monitor their health condition. Through qualitative and quantitative analyses, we will investigate participants' perceptions of these interactions, including their comfort levels, trust in the robot's capabilities, and overall satisfaction with the monitoring process.

- **RQ2: Can participants effectively understand and respond to various LED light patterns and gestures (hand and head movement) from the Nao robot?**
This research question will involve assessing participants' understanding and responsiveness to different nonverbal cues, such as LED light patterns and gestures, employed by the Nao robot. Insights gained from this investigation will inform the design and implementation of nonverbal communication strategies for robotic caregivers in healthcare contexts.

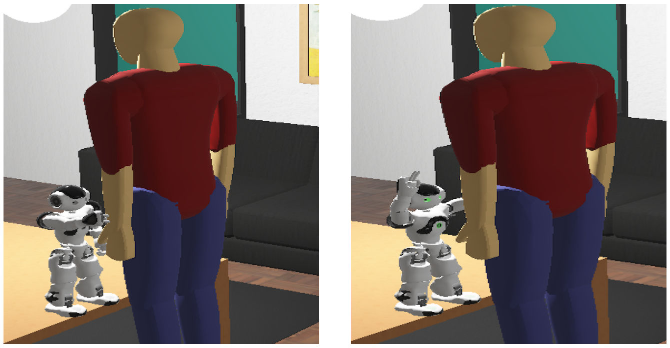
- **RQ3: What distinguishing factors influence trust between interactions involving human-human versus human-robot dynamics, specifically between older adults and care providers?**
This question delves into understanding the factors that shape trust in interactions involving older adults and robotic caregivers compared to those involving human care providers. Through qualitative research, we will explore the nuances of trust dynamics in these interactions, considering factors such as perceived empathy, reliability, and communication effectiveness. The findings will contribute to developing guidelines that foster trust and rapport in human-robot interactions within healthcare settings, particularly among older adult patients and their care providers.

IV. Methods

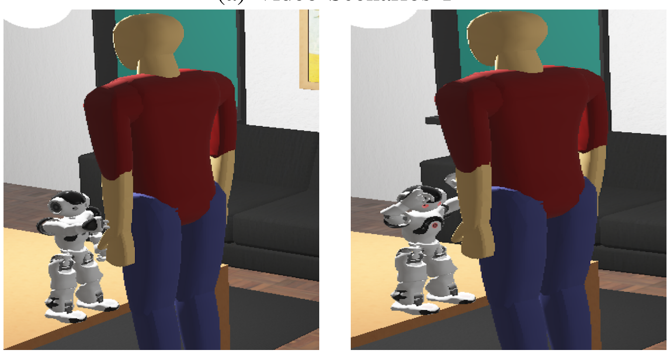
A. Overall Design

We designed our overall scenario using Webot due to the lack of Nao at the testing location. We utilize Google Forms to develop an online user study and make it accessible for participants to record responses based on simulation videos. These videos were recorded using the Webots simulation tool, showcasing the various nonverbal cues: touch, hand and head gestures, and LED patterns. In this setup, the environment consists of the Nao robot placed within an apartment with elderly adults (refer to Fig.1). To simulate realistic interactions between older adults and the robot, we have devised two representative scenarios. The Nao robot interacts with older adults to monitor people's health conditions. Fig. 2 shows screenshots from each scenario. The simulated scenarios utilized for our research are outlined below:

- **Scenario 1: Positive Responses**: In an apartment, an elderly individual stands in front of the Nao robot po-



(a) Video Scenarios-1



(b) Video Scenarios-2

Fig. 2. Two types of simulated scenarios: (a) Positive reponse and (b) negative response.

sitioned on a table. The Nao robot's primary responsibilities include assisting and monitoring the elderly's health conditions. Utilizing GPS location, Nao moves towards the elderly individual's hand to check their health condition through touch. If the health condition is deemed satisfactory, Nao expresses a positive response. This is achieved by changing its LED lights to green, raising its arms in a welcoming gesture, and nodding its head up and down in a reassuring manner.

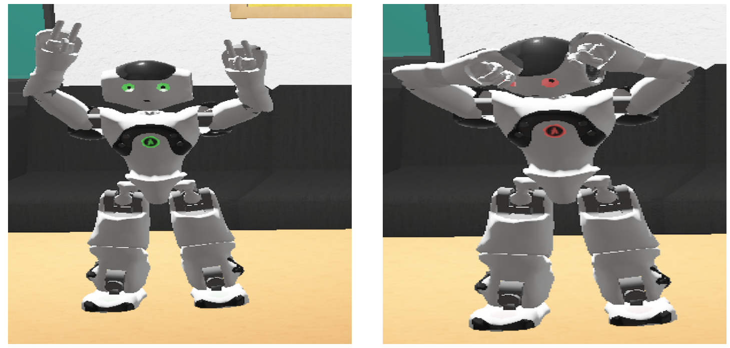
- **Scenario 2: Negative Responses**: This is the exact same setting as scenario 1. Nao robot touches the elderly individual's hand again to check the health condition. If the health condition is not satisfactory, Nao expresses a negative response. This is achieved by changing its LED lights to red, lifting its arms to its head in a thinking gesture, and nodding its head left and right reassuringly.

In the two scenarios, we have implemented various non-verbal cues for HRI between the Nao robot and older adults. The non-verbal cues are:

- Touch by Nao robot
- Hand and head gestures by Nao root
- LED pattern used by Nao robot.

Manipulated Nao Touch Behavior: Nao has various basic commands and behaviours. We have manipulated the Nao behaviour based on our research question.

1) Touch Manipulation: Nao robot has nine tactile sensors and eight pressure sensors [19]. These tactile sensors can be used to monitor various signals, such as temperature, ECG, etc.

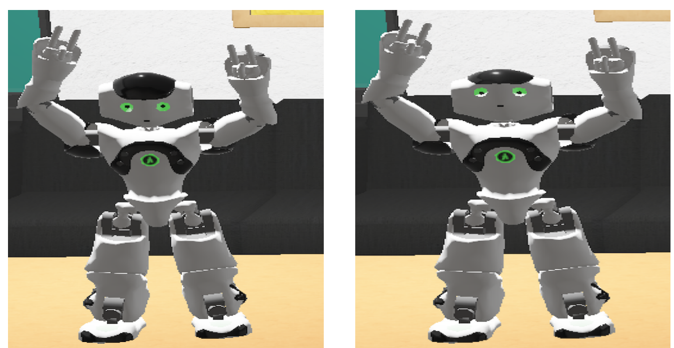


(a) (b)

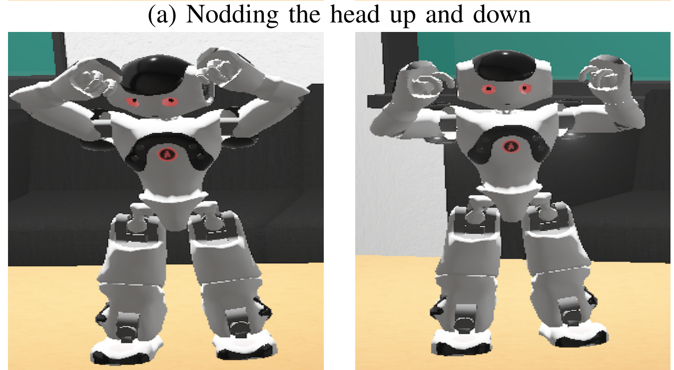
Fig. 3. Snapshot of the Nao robot displaying: (a) Positive gesture the robot raises its arms and (b) negative gesture the robot lifts its arm to its head.

However, as we created the project in a Webots simulation, it was challenging to manipulate the Nao sensors. Instead, in our project, we used the $rand()$ function, which generates either 1 or 0 when the Nao robot touches a human. When Nao generates a 1, it indicates a good health condition or positive vibes, and a 0 indicates a poor health condition or negative vibes.

2) Hand and Head Gestures Manipulation: In the Webots simulation environment, adjusting its visible outputs manipulated the robot's behavioural patterns. To achieve this, we utilized the $wbu_{m}otion_{n}ew$ function to control the behavior of the Nao robot. Initially, Nao is positioned as depicted in Fig. 1. For movement, Nao employs six basic commands:



(a) Nodding the head up and down



(b)Nodding the head left to right

Fig. 4. Snapshot of the Nao robot displaying: (a) Positive gesture and (b) Negative gesture.

$forward()$, $backward()$, $side\_by\_left()$, $side\_by\_right()$, $turn\_left\_60()$, and $turn\_right\_60()$. Nao uses these basic commands to navigate towards adult individuals. Additionally, we introduced three new hand gestures for health monitoring purposes, which are displayed through the robot's hand gestures. A handshake gesture was implemented to facilitate physical interaction with the adult individuals. When Nao receives a value of 1 from the $rand()$ function, it displays a positive gesture by raising its arms, as shown in Fig. 3(a). Conversely, when Nao receives a value of 0, it displays a different positive gesture by lifting its arms to its head, as illustrated in Fig. 3(b). The three new wbu_motion_new functions introduced for hand gestures are $handshake()$, $sadmotion()$, and $happymotion()$, respectively.

Additionally, two new head gestures, Nao, were implemented to convey expressions. When Nao receives a value of 1 from the $rand()$ function, it nods its head up and down, as depicted in Fig. 4(a). On the other hand, when Nao receives a value of 0, it nods its head from left to right and right to left, as shown in Fig. 4(b).

3) LED Patterns Manipulated: In the Webot simulation, the Nao robot has eight LED lights. We have manipulated the Nao robot's two eye LEDs and ChestBoard LED. Initially, all the LEDs are off. When Nao receives a value of 1 from the $rand()$ function, it shows the happy expression and changes the LED pattern from the initial to the $GREEN$ color in Fig. 5(a). When Nao receives a value of 0, it shows a negative expression and changes the LED pattern from the initial to the RED color in Fig. 5(b).

(a) GREEN color

(b) RED color

Fig. 5. Snapshot of the Nao robot displaying: (a) Positive gesture and (b) negative gesture.

B. Participants

The study was entirely conducted online, utilizing a Google Forms questionnaire that contained links to two simulation videos of a robot operating in an apartment. Email invitations and links were distributed among the class and classmates to recruit participants. Eight students, aged between 22 and 28 (with $ME = 24.75$ and $SD = 1.98$), from the University of Waterloo, participated in the study. Out of these, five identified as male and the rest as female. All participants had prior experience with robot interaction. We have employed a **mixed-methods approach** with a **within-subject factorial** design for assessing participant responses to different types of interactions and cues in the simulated scenarios (both scenarios and all types of nonverbal cues).

C. Artifacts

The Softbank Nao [20] robot is originally commercially available. However, since that robot is not readily available, a model of Nao in Webot was used to perform the experiments. We utilized this robot to interact with elderly adults and continuously monitor their health condition. To establish nonverbal communication, the Nao robot will use touch, hand, and head gestures, as well as LED patterns. We added new touch gestures, such as $handshake()$. We implemented the $sadmotion()$ and $happymotion()$ for hand and head gestures. We modified $set\_led\_color()$ for LED patterns to either green or red. We modified the existing controller of Nao and implemented new behaviour patterns using the C programming language. The modified controller file is attached in the appendix section.

D. Procedures

When the experiment starts, participants are requested to provide demographic details and complete a survey evaluating the Nao robot on its non-verbal cues. The survey is structured into three parts: gathering demographic data, exploring robot communication scenarios, and a section dedicated to human-robot interaction. Participants are shown two video scenarios featuring a robot caregiver conducting a medical screening. Following each video, they are asked to fill out a survey to record their impressions of the interaction. In the next section, we briefly describe our measurement parameters.

E. Measures

The research questions aimed to evaluate participant experiences and perceptions in three main domains: **perception**, **nonverbal communication efficiency (either LED or hand gesture** and **trustworthiness**. Questionnaire items were assessed participant agreement on a 5-point **Likert scale ranging** from 1 *(Strongly Disagree)* to 5 *(Strongly Agree)*. We have employed a **mixed-methods approach** with a **within-subject factorial** design for assessing participant responses based on 4 independent variables and 11 dependent variables.

1) Perception (for RQ1): Participants assessed specific aspects of Nao's touch-based health monitoring, including **trackability**, **comfortability**, **competency**, and **reliability** (dependent variables). They also evaluated the ease of comprehension, comfort, confidence in data accuracy, and perceived reliability of the system.

2) Efficiency of Nonverbal Communication (for RQ2): Participants assessed the **effectiveness**, **understandability**, and **accuracy** (dependent variables) of Nao's LED light or hand and head movement gestures, which are key elements of its nonverbal communication.

3) Trustworthiness (for RQ3): Participants provided feedback on the following topics: the impact of interaction (**interactivity**) length on trust dynamics, perceived empathy and communication effectiveness (**relationship dynamics**) in human-robot interactions, **dependence** on interaction type for care needs and **trust level** in human-robot interactions.

V. Results

In this section, we present the results of our study, which involved a quantitative analysis of participants' responses to assess the effectiveness of nonverbal communication modalities used by Nao robots in healthcare settings. The study utilized a mixed-methods approach, incorporating statistical analysis ($t - test$) and survey-based evaluations to evaluate participant perceptions comprehensively.

A. Perception (RQ1)

Participants rated Nao's touch-based health monitoring positively across several dimensions. They found it easy to understand ($ME = 3.75$, $SD = 0.46$), indicating clear comprehension of its purpose and method. Comfort levels were moderate ($ME = 3$, $SD = 0.93$), with some variability in responses. Confidence in Nao's competency was moderate as well ($ME = 3$, $SD = 0.76$), suggesting trust in its ability to monitor health accurately. Perceived reliability was generally high ($ME = 3.625$, $SD = 0.74$), indicating trust in the system's consistency. Overall, participants viewed Nao's touch-based health monitoring favourably, with a scope for enhancing comfort and confidence levels further. Fig. 6 shows the perception of touch against various dependent variables.

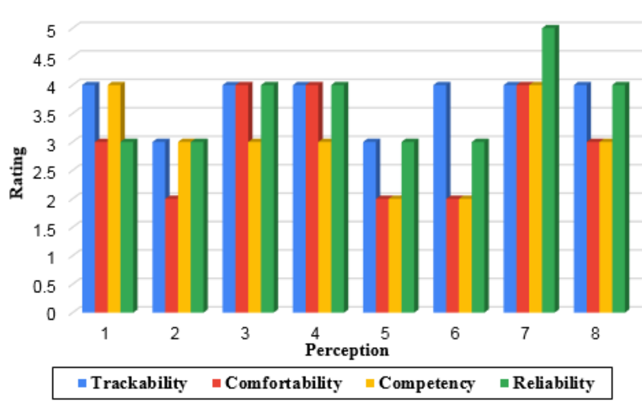


Fig. 6. Perception of touch rated against trackability, comfortability, competency, and reliability.

B. Efficiency of Nonverbal Communication (RQ2)

To determine which gesture (hand and head gestures or LED patterns) is perceived as better for each dependent variable, we need to consider both the significance level ($p-$value) and the effect size (Cohen's d). For Effectiveness: $p-$value $= 0.133$ (not significant at $\alpha = 0.05$), Cohen's $d = 0.5/0.675 \approx 0.741$ (medium to large effect size), Understandability: p-value = 0.020 (significant at $\alpha = 0.05$), Cohen's $d = 0.5/0.472 \approx$ 1.058 (large effect size), Accuracy: $p-$value = 0.005 (significant at $\alpha = 0.05$), Cohen's $d = 0.75/0.502 \approx 1.493$ (large effect size). Therefore, based on Table 1, **LED patterns are perceived as better than hand and head gestures** in terms of understandability and accuracy. For effectiveness, although the $p-$value is not significant, LED patterns still show a medium to large effect size, indicating a potential preference for LED patterns.

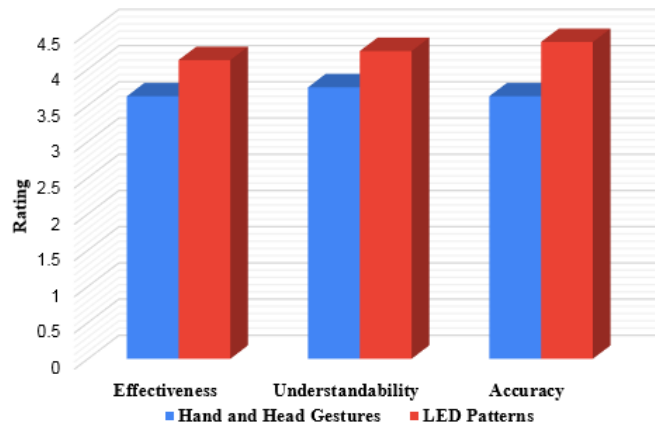


Fig. 7. Non-verbal communication efficiency (either LED or hand gesture approaches) rated against effectiveness, understandability and accuracy.

TABLE I
STATISTICAL DESCRIPTION FOR NON-VERBAL COMMUNICATION EFFICIENCY OF LED APPROACHES OR HAND AND HEAD GESTURES.

Evaluation	Effectiveness	Understandability	Accuracy
$p-$value	0.133	0.020	0.005
$t-$value	1.694	3.055	4.098
Effect size	0.742	1.058	1.493
LED ME$\pm$SD	4.12 $\pm$ 0.83	4.25 $\pm$ 0.46	4.37 $\pm$0.51
H&H ME$\pm$SD	3.62$\pm$0.48	3.75$\pm$0.48	3.62$\pm$0.53

* H&H = Hand and Head gestures, ME = Mean value, SD = standard deviation.

C. Trustworthiness (RQ3)

Participants' trust dynamics varied significantly with the length of interaction. Longer interactions generally led to higher trust levels, as evidenced by the increasing trend observed in Fig. 8. The $ME = 3.62$, with $SD = 0.51$, indicating a moderate variation in responses. Participants perceived high empathy and effective communication in human-robot interactions, particularly in longer interactions. This was reflected in the high ratings in the Fig. 8, with $ME = 3.87$ and $SD = 0.35$, indicating a small variation in responses. Participants showed varying degrees of dependence on human-robot interactions for their care needs. The mean score for dependence on interaction type for care needs was 3.875, with a standard deviation of 0.64, suggesting a moderate response variation. However, the level of dependence on the robot for care needs varied among participants, indicating the necessity for personalized approaches in human-robot interactions in healthcare settings. On the other hand, Fig 9 shows that most participants recommended the Nao robots as caregiver instead of human caregiver.

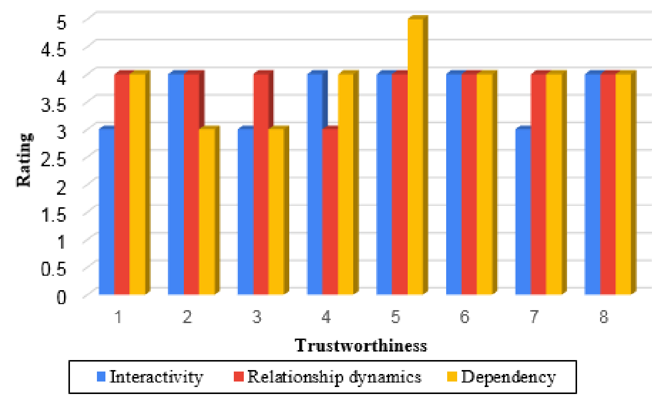


Fig. 8. Trustworthiness rated against interactivity, relationship dynamics, and ndependency.

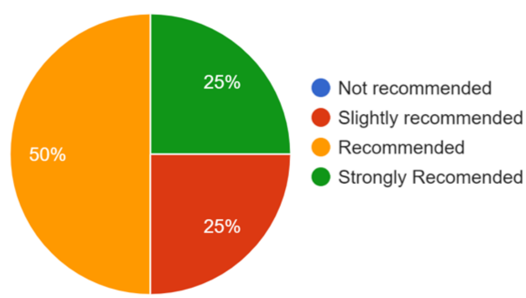


Fig. 9. Percentage of participants against the trust level for recommendation of the Nao robot for health monitoring.

VI. Discussion

The analysis of our study's findings reveals promising insights into the efficiency of non-verbal communication facilitated by Nao in healthcare settings. Participants generally perceived Nao's touch-based health monitoring as easy to understand, moderately comfortable, competent, and reliable. These positive perceptions align well with our research question on non-verbal communication efficiency, supporting the clarity and effectiveness of Nao's touch gestures in conveying health-related information. Despite slight variability in comfort levels, the overall favorable responses highlight the effectiveness of Nao's touch-based communication in fostering patient understanding and engagement during healthcare interactions.

Furthermore, our comparison of LED patterns and hand/head gestures for non-verbal communication efficiency yielded significant differences. LED patterns exhibited a medium to large effect size, indicating their potential advantage despite a non-significant $p-$value. Notably, LED patterns were significantly favoured in terms of understandability and accuracy, suggesting clearer comprehension and greater precision in conveying intentions compared to gestures. These findings strongly support our research question on non-verbal communication effectiveness, underscoring the superiority of LED patterns for enhancing communication clarity and accuracy in human-robot interactions.

Moreover, our analysis of participants' responses to RQ3 underscores the crucial role of interaction length in shaping trust dynamics. Longer interactions correlated with increased trust levels, emphasizing the importance of prolonged engagement in fostering trust between participants and Nao. Participants consistently perceived a high level of empathy and effective communication in human-robot interactions, particularly during extended interactions, highlighting the reliability of Nao's non-verbal communication cues in fostering trust. Additionally, participants exhibited varying degrees of dependence on human-robot interactions for their care needs, further emphasizing the importance of non-verbal communication efficiency in reinforcing trust dynamics and supporting the overall objectives of our study.

VII. Conclusion

Our study investigated the potential of using humanoid robots, Nao, for health monitoring and caregiving for older adults. Through a combination of nonverbal communication modalities, including touch, gestures, and LED patterns, we aimed to enhance the quality of human-robot interactions and improve the overall experience for older adults receiving care. Our findings suggest that Nao's touch-based health monitoring was generally well-received by participants, with positive ratings across various dimensions such as trackability, comfortability, competency, and reliability. Participants viewed Nao's touch as easy to understand and generally reliable, indicating a promising avenue for integrating robots into healthcare settings. Furthermore, our analysis of nonverbal communication efficiency revealed that LED patterns were perceived as more effective and accurate than hand and head gestures. Although LED patterns showed a medium to large effect size for effectiveness, the significant differences in understandability and accuracy underscored their potential advantage in conveying clear and precise messages in human-robot interactions. Moreover, our investigation into trustworthiness highlighted the importance of interaction length in shaping trust dynamics between participants and Nao. Longer interactions were associated with higher trust levels and perceived empathy and communication effectiveness, indicating the critical role of prolonged engagement in fostering trust and rapport in human-robot interactions. By leveraging nonverbal communication modalities and fostering trust in human-robot interactions, we aim to improve the quality of life for older adults and address the challenges associated with traditional caregiving methods. However, it is important to acknowledge the limitations of our study, including the small sample size and the use of a simulation environment. These limitations may restrict the generalizability of our findings and underscore the need for further research in real-world healthcare settings.

VIII. Limitations and Future Work

In this study, we delved into the realm of nonverbal interactions involving a Nao robot and elderly adults, including various nonverbal cues such as touch, hand and head gestures, and LED patterns. The results, while preliminary, hold great promise, igniting a beacon of hope for the future of human-robot interactions in healthcare.

Moreover, the study faced some limitations. Firstly, the sample size in this study is very small, which could compromise the generalizability of the findings. The small sample size might limit the generalizability of findings and increase the risk of sampling bias. Furthermore, the recruitment of participants from a single institution might result in a lack of diversity in demographic characteristics. In future studies, efforts should be made to expand participant recruitment to include a more diverse range of demographics, such as age, gender, and cultural background. Expanding the sample size to include a larger and more diverse population would enhance the generalizability of the findings. Secondly, the use of Webots simulation might not fully replicate the complexity and dynamics of real-world healthcare environments. Manipulating Nao's behaviors in the simulation could introduce biases or artificiality into participant interactions. Moreover, conducting the study without ethical approval raises ethical concerns regarding participant consent and data privacy. Future studies could focus on developing more realistic simulation models that closely mimic real-world healthcare settings to address these limitations. Incorporating naturalistic observations of human-robot interactions in real healthcare environments could complement simulation-based studies. Additionally, obtaining ethical clearance before conducting future studies is essential to ensure compliance with ethical guidelines and protect participant rights. Finally, in terms of research questions, the formulated inquiries might cover only some pertinent aspects of integrating robotic caregivers into healthcare settings. Focusing solely on specific nonverbal communication cues may overlook other critical factors influencing human-robot interactions. Moreover, biases in participant responses due to the framing of research questions or the simulation environment could impact the validity of the results. Future research endeavours should aim to broaden the scope of research questions to encompass a more comprehensive range of factors influencing the integration of robotic caregivers in healthcare.

IX. Acknowledgement

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