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The Robot Screener Will See You Now: A Socially Assistive Robot for COVID-19 Screening in Long-Term Care Homes

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Abstract— **The rapid spread of COVID-19 around the globe has increased the need to adopt autonomous social robots within our healthcare systems. In particular, socially assistive robots can help to improve the day-to-day functioning of our healthcare facilities including long-term care, while keeping residents and staff safe by performing repetitive tasks such as health screening. In this paper, we present the first human-robot interaction study with an autonomous multi-task socially assistive robot used for non-contact screening in long-term care homes. The robot monitors temperature, checks for face masks, and asks screening questions to minimize human-to-human contact. We investigated staff perceptions of 7 attributes: screening experience without and with the robot, efficiency, cognitive attitude, freeing up staff, safety, affective attitude, and intent to use the robot. Furthermore, we investigated the influence of demographics on these attributes. Study results show that, overall, staff rated these attributes high for the screening robot, with a statistically significant increase in cognitive attitude and safety after interacting with the robot. Differences between gender and occupation were also determined. Our study highlights the potential application of an autonomous screening robot for long-term care homes.**

I. Introduction

Due to the rapid spread of COVID-19 in the community, the presence of social robots has increased in places such as: 1) hospitals, where they are used to check for elevated temperature and allow staff to remotely monitor patients [1], [2], and 2) long-term care (LTC) homes, where they let family members stay in touch with patients via telepresence [3]. A major advantage of using non-contact social robots is they help reduce the transmission of viruses by minimizing person-to-person contact and can be easily disinfected [4].

In general, there have been staff shortages in both LTC homes and hospitals pre-pandemic [5], however, the COVID-19 pandemic has escalated these shortages to a critical level [6]. Staffing shortages not only impact vulnerable residents and patients, but also staff members. In [7], a survey conducted during the COVID-19 outbreak with caregivers aiding dementia residents found that half of them reported higher levels of stress and exhaustion. In [8], a study on staff working in a LTC home during COVID-19 found they experienced psychological stress from contracting or spreading the virus, and from seeing residents in prolonged confinement. Furthermore, during the pandemic, healthcare facilities have needed to enforce strict requirements for staff to implement in addition to their existing duties.

A handful of social robots have been deployed to assist in COVID-19 screening tasks. To-date, these robots can perform a limited number of screening tasks separately, such as: checking temperature [9], providing safety instructions and mask detection [10]. Exceptions being the Misty II robot, which takes both temperature and asks screening questions [11], and the Cruzr robot which takes temperature and checks for face masks [1]. To the authors' knowledge, there are no reported human-robot interaction (HRI) studies yet on the efficiency, acceptance, and use of such screening robots.

In this paper, we present the first HRI study with a socially assistive robot for autonomous screening in healthcare applications. The robot is uniquely able to perform multiple screening and administrative tasks, to help front desk staff. These tasks include temperature taking, mask detection, identification of staff through QR code, and validation of screening questions. Furthermore, the robot can alert facility administrators in real-time of failed screening results, and stores pass/fail results to be shared regularly with administrators and public health units as required. We present results and insights from our ongoing HRI study, where our autonomous interactive screening robot is deployed at the entrance of a LTC home during the COVID-19 pandemic.

II. Related Work

In this section, we discuss the different tasks that social robots have performed in LTC homes and hospitals during the pandemic. We present HRI studies with COVID-19 safety monitoring robots and discuss pre-pandemic HRI studies on healthcare staff perceptions of social robots.

A. Robots Helping During COVID-19 in Healthcare

Social robots have been deployed in healthcare settings during the pandemic, for: 1) reducing social isolation and loneliness through telepresence [12], [13]; 2) triaging of incoming patients [2], and 3) disinfecting surfaces and temperature monitoring [14].

In [12], the Temi robot was used for virtual calls between residents of nursing homes or a geriatric hospital and their relatives. Results showed that the frequency of robot use increased, and in the hospital setting patient loneliness decreased overall. Positive feedback was received from all user groups (residents, relatives, and nursing staff) involved.

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The expressive ARI robot was introduced in [13] with the potential to help with tasks during COVID-19, in hospitals and home-care settings, including engagement in cognitive games, providing reminders, and initiating video calls with family.

In [2], the Spot quadruped robot facilitated the acquisition of vital signs and performed brief contactless interviews to reduce exposure of hospital staff to incoming patients in a triage tent. The robot was retrofitted with a tablet for medical interviews, and an infrared (IR) camera and 3 monochrome cameras to remotely measure incoming patients' vital signs.

In [14], the Lio robot was adapted to perform COVID-19-related tasks in a hospital. Its robotic arm was used to grasp and carry a UV-C light to disinfect surfaces tagged with ArUco markers for the robot to find. The gripper could also hold an IR camera coupled with an RGB camera, to detect if people in common areas had elevated body temperatures; Lio would then notify a staff member to follow up.

B. HRI Studies with Safety Monitoring Robots

HRI studies have mainly focused on COVID-19 safety in non-healthcare environments, such as university campuses [15], and urban streets and parks [16]. For example, in [15], the Temi robot detected if people entering a university campus building would comply with COVID-19 guidelines/restrictions. Results found that design manipulation, such as the addition of flashing lights, did not significantly affect compliance or avoidance but did decrease prolonged interaction with the robot.

In [16], a quadruped surveillance robot monitored adherence to social distancing rules in crowded outdoor urban environments (e.g., university campus or park). The robot provided distancing suggestions using three gendered voices (computer-generated neutral voice; human male and female voices); and a child (female) voice. It was found that half the participants followed the robot's social distancing suggestions, while the rest ignored the robot or walked away. An HRI study conducted found acceptance, perceived trust, and attitude towards the robot to be higher for a female voice than for a male voice. Female participants also scored the neutral voice more positively.

C. HRI Studies with Social Robots and Staff in Healthcare

Pre-pandemic HRI studies with caregivers have mainly focused on attitudes and acceptance of social robots providing entertainment, facilitating cognitive interventions, and health monitoring [17]–[20]. For example, in [17], the robot Tangy learned recreational activities from caregivers using learning from demonstration, in order to autonomously facilitate Bingo games with elderly residents in LTC homes. Both caregivers and residents had an overall positive experience using Tangy.

In [18], caregivers' attitudes toward several home healthcare robots were investigated in both Finland and Japan. The study found culture influenced caregivers' perceptions of the robots and the perceived importance of their tasks. Namely, Japanese caregivers assessed robot usefulness more positively than the Finnish caregivers, and Finnish care personnel had certain fears, such as robots making treatment of older adults inhumane, or that their introduction would add to the loneliness of older adults.

In [19], the Guide and Cafero telepresence robots provided entertainment, telepresence, and health-monitoring functions in an aged care facility. Staff members found the robots to be useful for these tasks and had more positive responses towards the robots than the residents. Staff also used the robots more often, by initiating resident activities.

In [20], a pilot placement with the Pepper robot in a home care work unit investigated the impact of activities with robots (memory stimulation of older adults, listening to the news, and an email-based messaging service) on care workers' attitudes. Changes in the test group (staff who took part in the intervention with the care robots) were compared to changes in the control group (no intervention). Perceived robot usefulness was significantly higher for the test group; and they had more positive views of robots offering practical assistance.

In general, social robots have the potential to assist LTC staff with both resident care tasks and staff-related tasks. As was made evident during the pandemic, LTC homes are high-risk environments with vulnerable populations. Thus, screening, detection and reporting of COVID-19 symptoms is paramount to minimize outbreaks. During the pandemic, additional front desk staff were needed for screening all incoming visitors and staff members.

There have not yet been any HRI studies focused on autonomous robot screening within a healthcare facility during the pandemic. Furthermore, to the authors' knowledge, the direct interaction of staff in LTC with a screening robot that everyone interacts with as a point of entry has not yet been explored. In LTC homes, a large population of staff with different roles have the opportunity to interact with a screening robot, thus providing a unique opportunity for access to a technology that may have not been available pre-pandemic. In general, staff acceptance is an important factor in the deployment of new technology such as robotics in a healthcare facility and building a robot-positive care culture.

In this paper, we present the first exploratory HRI study conducted during the COVID-19 pandemic that investigates the utilization and effectiveness of a social interactive screening robot in a LTC setting. Furthermore, we evaluate staff members' overall experiences with such a robot for a daily repetitive but critical task which impacts everyone. We also uniquely explore how staff demographics influence their attitudes and their intent to use a robot.

III. Robot Screening Study

We conducted a study over the course of two months at a local LTC home in Toronto, Canada, with the Pepper robot. Pepper was situated at the front entrance of the home in front of the reception area. The study was approved by the University of Toronto's ethics board. Participants gave written consent and were provided with a unique QR code to use for the screening task.

A. Robot Design for Screening and Monitoring Tasks

A contactless thermometer was placed on a stand next to Pepper to detect and record staff temperature readings, as seen in Fig. 1. A graphical user interface (GUI) was developed using HTML for Pepper's tablet during the screening interaction. The GUI was used to complement the robot's speech during screening with corresponding text and confirmation images. A progress bar was displayed at the top of the screen to indicate screening progress. The robot's forehead RGB camera was used for both face mask and QR code detection. AIZoo Tech's FaceMaskDetection software [21], which uses convolutional neural networks, was adapted for mask detection. It detects if multiple people are in the robot's sensing range, and our program then generates an exception with Pepper instructing users to maintain social distancing. Pepper's Barcode Reader software is used to detect the unique QR codes. Each screening event is time-stamped, and contains the QR code, temperature reading, face mask confirmation, and screening answers, which are logged in a CSV file and emailed by the robot to administrative staff following each failed screening, and at the end of the week for everyone else.

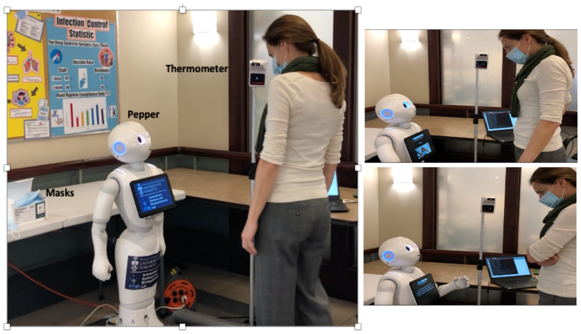

Figure 1. Pepper set-up at the LTC home (left), Pepper detecting masks and asking screening questions (right)

A finite state machine was developed for the overall screening task, as shown in Fig. 2. A video of Pepper conducting the screening procedure is provided on our YouTube channel https://www.youtube.com/watch?v=X6EKXENu9bY.

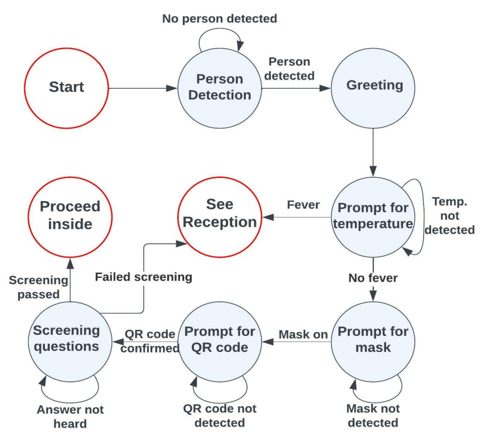

Figure 2. Robot Screening Finite State Machine

B. Participants

Participants were recruited from among the staff members at the LTC home. Study flyers were placed at the front desk and in elevators, and a short introductory Pepper video was emailed by management to the staff. Pepper was stationed in the lobby of the home for a few days prior to the study, so staff could see the robot and ask questions of the research team.

C. Procedure

Robot COVID-19 screening occurred with staff in two different shifts (6:30 am and 2:30 pm). As they entered the front doors, they would first be screened by Pepper. The average robot screening time was 80 s. There was a human screener at the reception desk for when the robot asked staff members to see reception, and in case robot screening failed. The robot stayed at the entrance from 6:30 am to 3:30 pm each day that the screening took place.

D. Measures

Pre-study and post-study questionnaires were completed by participants to obtain demographic information (age range, gender, occupation). They also included 5-point Likert questions (5=strongly agree, 3=neutral, 1= strongly disagree) that focused on screening experience, perceived efficiency, cognitive attitude, freeing up staff, perceived safety, affective attitude, and intent to use the robot for the task, as shown in Table I. The questions for attitude, perceived enjoyment, and intent to use were adapted from the Almere model [22]. A question about previous robot experience (no experience, beginner, intermediate, advanced) was also included. We analyzed the pre- and post-study data overall and with respect to demographics to determine statistically significant effects.

TABLE I: PRE/POST STUDY QUESTIONS

Questions Pre-Study (Post-Study)	
Q1 **(screening experience)**	I have had a good experience with the way **the health screening (the robot health screening)** is being conducted at Yee Hong
Q2 **(efficiency)**	**It would be (it is)** more efficient if the screening **was done (is done)** automatically with the robot
Q3 **(cognitive attitude)**	I think having a robot ask COVID-19 health screening questions **would be (is)** a good idea
Q4 **(freeing up staff)**	Using a robot **would (did)** free up staff that need to do the screening
Q5 **(safety)**	I think a robot **would make (makes)** the health screening process safe
Q6 **(affective attitude)**	I think a robot **will make (makes)** the screening process enjoyable
Q7 **(intent to use)**	I **would (would continue to)** use a robot to do the COVID-19 screening at Yee Hong

IV. RESULTS

Our HRI study investigated care staff's expectations prior to interacting with the autonomous COVID-19 screening robot and their overall experience directly interacting with the robot. In total, 56 participants completed the pre-study questionnaire prior to interactions, 31 women, 8 men, 0 as other, and 17 participants did not specify a gender. Participants provided their ages in one of five groups: 20-29, 30-39, 40-49, 50-59, and 60+. They reported their occupation as: physiotherapist, occupational therapist, social worker, recreational coordinator, administrator, personal support worker (PSW), and nurse. Of these participants, 27 participants completed the post-study questionnaire (15 women, 11 men, 0 as other, and 1 did not specify a gender). We conducted a series of Shapiro-Wilk tests of normality, and concluded our data was non-parametric (p<0.05).

We compared overall pre- and post-study responses to investigate if there were changes in the 7 attributes listed in Table 1. Results are presented in Fig. 3. In general, participants' scores were consistently high for all seven questions pre- and post-study ($\tilde{x}$=4), with an increase to $\tilde{x}$=5 for Q3 and Q5 post-study. Namely, for Q3, a statistically significant difference was found after participants interacted with Pepper ($\tilde{x}$=5, IQR=1) than prior to interacting with the robot ($\tilde{x}$=4, IQR=2); WSR test Z=2.060, p=0.039.

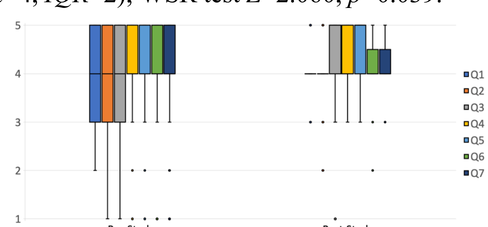

Figure 3. Box and whisker plot of pre and post results for all participants

While no statistically significant difference was found for Q5, WSR test Z=1.906, p=0.057, participants responded more positively to this question after interacting with Pepper ($\tilde{x}$=5, IQR=1) than prior to interacting with the robot ($\tilde{x}$=4, IQR=1).

We also explored the effects of age, gender, occupation, and previous robot experience on the aforementioned seven attributes (Q1-Q7), which are discussed in detail below.

A. *Participant Demographics: Age*

Of the 56 participants who completed the pre-study questionnaire, 9 did not specify an age range. The pre-study (n=47) age distribution was 20-29 (n=3); 30-39 (n=5); 40-49 (n=18); 50-59 (n=19); and 60+ (n=2). Whereas the post-study (n=27) age distribution was 30-39 (n=4), 40-49 (n=6), 50-59 (n=13), 60+ (n=4). Pre-study, the median age group was 40-49, and post-study it was 50-59, as there were no participants in the 20-29 age range. Overall, there were no differences between subjects pre- or post-study as determined by KW tests (p>0.05). Furthermore, we compared within-subject questionnaire results prior to and after having interacted with the robot. No statistically significant difference was found within-subjects as determined by WSR tests (p>0.05).

B. *Participant Demographics: Gender*

We investigated if there were any statistically significant differences between the two gender groups (men and women). We compared results between the two gender groups prior to interacting with the robot, Fig. 4, and after interacting with Pepper, Fig. 5. No statistically significant difference was found between-subjects as determined by MWU tests (p>0.05). When we compared within-subject questionnaire results prior to and after having interacted with the robot, a statistical significance was found for cognitive attitude (Q3) for men using a WSR test; Z=2.000, p=0.046. Namely, men had higher scores for Q3 after directly interacting with Pepper ($\tilde{x}$=5, IQR=1) than prior to interactions ($\tilde{x}$=4, IQR=0.25).

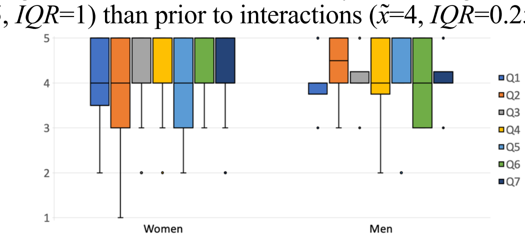

Figure 4. Box and whisker plot of pre-study results for gender

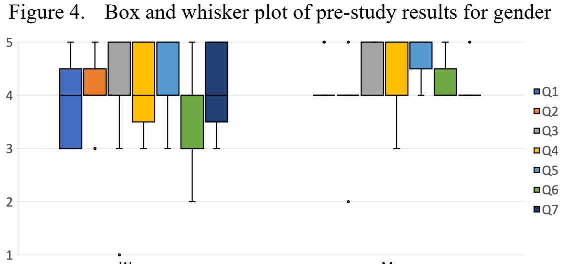

Figure 5. Box and whisker plot of post-study results for gender

C. *Participant Demographics: Occupation*

The various staff occupations reported were categorized into groups with similar roles: 1) Administrators (Admin) (pre-study n=11, post-study n=12), which included those working in human resources, reception, information technology, and management roles; 2) Nurses, including nurse practitioners, registered nurses, and registered practical nurses (pre-study n=8, post-study n=4); 3) Personal Support Workers (PSW) (pre-study n=14, post-study n=7); and 4) Rehabilitation & Social Care (RSC) (pre-study n=8, post-study n=4), including social workers, recreational/activation coordinators, physiotherapists, occupational therapists, and dieticians.

We compared results between subjects prior to, Fig. 6, and after interacting with Pepper, Fig. 7. No statistically significant differences were found in the results between these occupation roles, as confirmed by KW tests. When comparing within-subject results for the same occupation groups, the RSC group had a slightly higher median for Q2 (efficiency), prior to interacting with the robot ($\tilde{x}$=4, IQR=1) than after interacting with Pepper ($\tilde{x}$=3.5, IQR=1). A statistically significant difference was found for the RSC group, WSR test: Z=2.000, p=0.046. A statistically significant difference was also found for the RSC group for Q4 (freeing up staff), WSR test: Z=–2.000, p=0.046, where the group had a slightly higher median score prior to interacting with the robot ($\tilde{x}$=4.5, IQR=1) than after interacting with Pepper ($\tilde{x}$=4, IQR=0.25).

Statistical significance was also found for the PSW group pre- and post-study for Q5 (safety), WSR test: Z=2.070, p=0.038. In particular, the PSW group reported they thought a robot would make the health screening process safer after having interacted with Pepper ($\tilde{x}$=5, IQR=1) than prior to interacting with the robot ($\tilde{x}$=4, IQR=1.75).

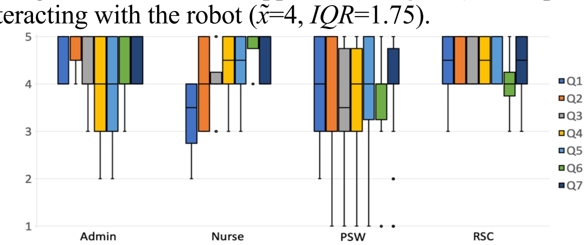

Figure 6. Box and whisker plot of pre-study results for occupation

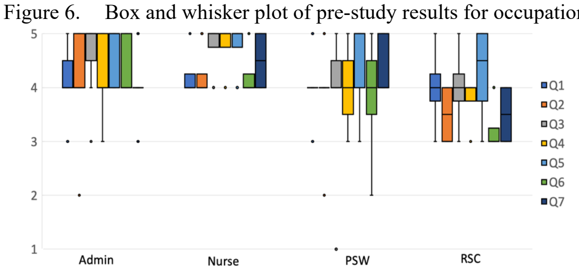

Figure 7. Box and whisker plot of post-study results for occupation

D. *Previous Robot Experience*

We investigated if previous experience with robots influenced participants' expectations of the screening robot. Participants selected from the following: 1) No Experience (n=11); 2) Beginner (n=10), seeing robots on TV or at museums; 3) Intermediate (n=4), seeing robots used at their workplace, delivering packages, or interacting with residents; and 4) Advanced (n=2), hands-on experience using a robot at work. Due to the small distribution within the latter groups, we grouped the responses into three categories: those with no prior experience at all (n=*11*), beginners (n=10), and those with at least some previous experience (n=*6*), Fig. 8.

A statistically significant difference was found for Q2 (efficiency) between subjects using a KW test: $H(2)$=6.018, p=0.049. Post-hoc non-parametric MWU tests with Bonferroni correction of α=0.016 showed the statistically significant difference to be between the Beginner ($\tilde{x}$=4, IQR=1, min=2, max=5) and No Experience ($\tilde{x}$=4, IQR=1, min=4, max=5) groups: U=26.5, Z=–2.244, p=0.043, r=0.49. There was no statistical significance found between the No

Experience ($\tilde{x}$=4, *IQR*=1, *min*=4, *max*=5) and Some Experience ($\tilde{x}$=4, *IQR*=0, *min*=4, *max*=5) group, p>0.5, or between Beginner ($\tilde{x}$=4, *IQR*=1, *min*=2, *max*=5) and Some Experience ($\tilde{x}$=4, *IQR*=0, *min*=4, *max*=5) group, p>0.5.

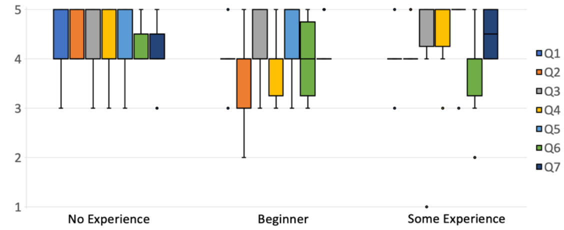

Figure 8. Box and whisker plot of results for previous robot experience

V. Discussions

The aim of our HRI study was to explore LTC staff perceptions of an autonomous robot deployed to help with COVID-19 screening during the pandemic. In particular, we explored staff opinions on the aforementioned 7 main attributes. We also investigated the effects of age, gender, occupation, and previous robot experience on these attributes.

A. *Cognitive Attitude*

Cognitive attitudes reflect people's beliefs, knowledge and thoughts [23]. In our study, there was a statistically significant positive increase in cognitive attitude (Q3) amongst all participants after robot interaction. This was consistent regardless of age and gender. In general, HRI studies have shown that direct repeated interaction with a social robot can positively influence people's cognitive attitudes towards a robot, as people become more familiar with it [24] and begin to experience its usefulness directly [20]. Even though creating a technology-positive culture within an organization is a long-term process [20], we postulate that the COVID-19 pandemic has accelerated a positive shift in staff attitudes towards robots. Specifically, in a pandemic situation where human contact is limited or prohibited, social robots can be beneficial [25] and potentially improve the working conditions of care workers [26]. The restriction of person-to-person contact has created an opportunity for robotic technology to help minimize the health risks of healthcare staff and vulnerable older adults. This was evident in the strong positive association we found between cognitive attitude and safety, affective attitude, and intent to use the robot. We believe this could be due to stress and anxiety induced by the pandemic. Namely, if a robot is able to perform certain repetitive and time-consuming tasks safely (such as screening), people will be more inclined to use it.

B. *Safety*

Perceived safety is a user's perception of the level of danger and their comfort during HRI [27]. Factors influencing safety include comfort, experience/familiarity, predictability, sense of control, and trust [28]. In our HRI study, safety was directly related to health during the COVID-19 pandemic. Staff already believed the social robot would make the screening process safe for them prior to robot interaction. This was further validated when they rated safety even higher after interaction with Pepper. Perceived safety was consistent between genders and across all age and occupation groups. In the context of the current pandemic, since the robot is used in a contactless manner, it helped minimize the risk of spreading the virus through person-to-person contact at first entry into the LTC building. When directly interacting with Pepper, staff were able to observe this safe interaction for themselves, which we postulate is the reason for the increased safety score.

As robots become more familiar to them, people's attitudes become more positive [18]. In fact, we observed several staff members coming back to do the screening with the robot at the end of their shifts when they could spend more time with Pepper. We found a strong positive association between safety and affective attitude, and between safety and intent to use. Namely, if staff perceive the robot as making the screening process safe, they are more likely to enjoy using the robot and continue using it.

C. *Age and Gender*

In our study, we found that men had a greater positive change in cognitive attitude after having interacted with the robot. However, men and women did not have any significant differences for the other 6 attributes investigated. Previous studies have found that men, in general, are more positive towards the use of robots [29], including in healthcare [30].

Similarly, previous HRI research has found that age does not influence attitudes and acceptance of social robots [23], [30]. While individual age has shown to have little influence on attitudes toward robots, societies with a large older adult cohort have been more supportive of robotic assistance [29].

D. *Occupation*

Our results show the Admin, Nurse, and PSW groups all had consistently high ratings across the 7 attributes. The PSW group showed a statistically significant positive increase in perceived robot safety for the screening task after interacting with Pepper. In their jobs, PSWs have a frontline, hands-on role with the residents of LTC homes and are perceived to have high risk of exposure during the pandemic. In addition, their own health, and the health of the many people in their care is consistently at risk, as they aid with bedside and personal care (helping people bathe, dress, and move), including during periods of illness. Interestingly, this result is different than non-pandemic studies that have found robot acceptance rated higher among those with managerial experience and higher educational levels [30]. It is also interesting to note that the RSC group had a slight decrease in their rating on both efficiency and freeing up staff after interacting with Pepper. This might be due to the lower number of RSCs (n=4) who filled out the post-study questionnaire compared to the RSC group (n=8) who completed the pre-study questionnaire.

E. *Previous Robot Experience*

People's perceptions can be influenced by a robot's observed and its perceived capabilities, usefulness, and potential role [31]. In our study, staff with no prior robot experience had a statistically significant difference for their rating of robot efficiency (Q2) for the screening task versus those with beginner experience. This difference with the no prior experience group could potentially be attributed to media exposure. Participants who had robot exposure through media, who may have exaggerated their capabilities, or have already seen robots exhibiting human-like behaviors, might have higher expectations of robots' actual capabilities. There is an expectation gap present when people attribute a human mental model with unrealistic expectations to social robots, leading to dissatisfaction [32]. People with no previous robot exposure may not have these expectations.

F. Considerations and Limitations

Our HRI study took place in a high-risk environment during the COVID-19 pandemic. Staff shortages due to COVID-19 could have impacted the number of participants during our study duration. The Omicron variant of the virus had the most impact as we had to abruptly end robot screening due to additional lockdowns. Therefore, we were only able to obtain 27 post-study questionnaires, which could have affected our overall results. However, robot deployment during the pandemic allowed staff to see firsthand a potential robot application in such stressful and understaffed times.

Cultural diversity was not accessed. The robot screening took place at a single site with mostly Asian staff members. As Toronto is a multi-cultural city, in the future, we will explore if culture influences social robot acceptance in LTC homes.

VI. Conclusion

Our HRI study deployed an autonomous health screening robot in a LTC home during the COVID-19 pandemic. We uniquely investigated staff opinions before and after interacting with a social screening robot, along with the effects of age, gender, occupation, and previous robot experience. Our results suggest that overall, participants rated all 7 attributes highly for the screening robot, showing autonomous screening with a robot as a potential application in LTC homes.

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