Assistive Robots to Support Older Adults: Interaction Design for Varying Levels of Automation

Thesis submitted in partial fulfillment
of the requirements for the degree of
"DOCTOR OF PHILOSOPHY"

by

Samuel A. Olatunji

Submitted to the Senate of
Ben-Gurion University of the Negev

April 14, 2021
Beer-Sheva

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Approved by the Advisors: Yael Edan Tal Oron-Gilad
Approved by the Dean of the Kreitman School of Advanced Graduate Studies

April 14, 2021

Beer-Sheva

This work was carried out under the supervision of

Prof. Yael Edan

and

Prof. Tal Oron-Gilad

in the Department of Industrial Engineering and Management,

Faculty of Engineering Sciences.

Research-Student's Affidavit when Submitting the Doctoral Thesis for Judgment

I, Samuel A. Olatunji, whose signature appears below, hereby declare that
(Please mark the appropriate statements):

- ☒ I have written this Thesis by myself, except for the help and guidance offered by my Thesis Advisors.

- ☒ The scientific materials included in this Thesis are products of my own research, culled from the period during which I was a research student.

- ☐ This Thesis incorporates research materials produced in cooperation with others, excluding the technical help commonly received during experimental work. Therefore, I am attaching another affidavit stating the contributions made by myself and the other participants in this research, which has been approved by them and submitted with their approval.

Date: 14/04/2021 Student's name: Samuel A. Olatunji Signature

Dedication

To my PARENTS, whose pursuit of knowledge, with the acumen of excellence, kept me inspired.

Bí a bá ṣe'ni lóore, ọpẹ́ là n dá.
Ọlọ́run á jẹ́ kí Ẹ pẹ́ fún wa. Ẹ máa jeun ọmọ pẹ́ lórúko Jésù.

To my WIFE, whose passion for intelligence, with life-transforming impact, kept me motivated.

Àríkẹ́ mi ọ̀wọ́n, Olorì t'Ọ́lọ́run fún mi kẹ́,
Mo ní ìfẹ́ ẹ̀ rẹ! Ọlọ́run á jẹ́ kí á sin ara wa jìnà.

To our newly ARRIVED BABY, whose birth, a few days to the final submission of this thesis, gave the thesis a truly joyful closing.

Ooreolúwa nì yìí,
Ayọ̀báyọ̀!

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List of Publications

Thesis journal publications

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J2. **Olatunji, S.**, Potenza, A., Oron-Gilad, T., Kiselev, A., Loutfi, A., Edan, Y. Levels of automation for a mobile robot tele-operated by a caregiver. *ACM Transactions on Human-Robot Interaction*. (submitted July 2020, minor revision submitted March 2021).

J3. **Olatunji, S.**, Oron-Gilad, T., Markfeld, N., Gutman, D., Sarne-Fleischmann, V., Edan, Y. Levels of automation and transparency: interaction design considerations in socially assistive robots for older adults. *IEEE Transactions on Human-Machine Systems* (accepted, July, 2021).

Journal publications related to the thesis in which I had major contributions

JR1. Honig, S. S., Oron-Gilad, T., Zaichyk, H., Sarne-Fleischmann, V., **Olatunji, S.**, & Edan, Y. (2018). Toward socially aware person-following robots. *IEEE Transactions on Cognitive and Developmental Systems*, 10(4), 936-954. https://doi.org/10.1109/TCDS.2018.2825641 [1]

JR2. Avioz-Sarig, O., **Olatunji, S.**, Sarne-Fleischmann, V., Edan, Y. 2020. Robotic system for physical training of older adults. *International Journal of Social Robotics*, 1-16. https://link.springer.com/article/10.1007/s12369-020-00697-y [2]

JR3. Gutman, D.; **Olatunji, S.**; Edan, Y. Evaluating Levels of Automation in Human–Robot Collaboration at Different Workload Levels. Appl. Sci. 2021, 11, 7340. https://doi.org/10.3390/app11167340 [3]

Manuscripts in preparation

JR4. Gutman, D., **Olatunji, S.**, Markfeld, N., Givati, S., Sarne-Fleischmann, V., Oron-Gilad, T., Edan, Y. 2020a. Evaluating levels of automation and feedback in an assistive robotic table clearing task for eldercare. In preparation for *Applied Ergonomics*. [3]

JR5. **Olatunji, S.**, Oron-Gilad, T., Edan, Y. Evaluating quality of interaction in robotic applications. In preparation for the *International Journal of Social Robotics*.

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[1] This publication is not part of the thesis, but is included in a parallel study where I contributed to the survey.
[2] This publication is not part of the thesis, but is included in a parallel study that was performed as part of the MSc thesis of Omri Avioz-Sarig where I contributed to the feedback design, experimental design, and writing.
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Conference peer reviewed and presented work

C1. **Olatunji, S.**, Oron-Gilad, T., Edan, Y. 2018. Increasing the understanding between a dining table robot assistant and the user. *International Ph.D. Conference on Safe and Social Robotics,* Madrid. http://www.socrates-project.eu/internal-documents/SSR_2018/SSR_2018_paper_24.pdf

C2. **Olatunji, S.**, Serna-Fleischmann, V., Honig, S. S., Zaichyk, H., Markovich, T., Oron-Gilad, T., Edan, Y. 2018. User preferences for socially acceptable person-following robots: environmental influence case studies. *Proceedings of Assistance and Service Robotics in a Human Environment Workshop, IEEE/RSJ International Conference on Intelligent Robots and Systems*, Madrid, Spain.

C3. Honig, S. S., Oron-Gilad, T., Fleischmann-Serna, V., **Olatunji, S.**, Edan, Y. 2018. A user-needs based approach for designing human-robot interactions. *Proceedings of Workshop on Robotic Co-workers 4.0: Human Safety and Comfort in Human-Robot Interactive Social Environments, IEEE/RSJ International Conference on Intelligent Robots and Systems*, Madrid, Spain.*

C4. **Olatunji, S.**, N. Markfeld, D. Gutman, S. Givati, V. Sarne-Fleischmann, T. Oron-Gilad, Y. Edan. 2019. Improving the interaction of older adults with a socially assistive table setting robot. *Proceedings of the International Conference on Social Robotics* (pp 568-577), 11876 LNAI Lecture Notes in Computer Science. Springer International Publishing.

C5. **Olatunji, S.**, Sarne-Fleischmann, V., Honig, S. S., Oron-Gilad, T., Edan, Y. 2019. Feedback design to improve interaction of person-following robots for older adults. *Proceedings of Mobile Robot Assistants for the Elderly, Workshop at the International Conference on Robotics and Automation (ICRA)*, Montreal, Canada, May 20-24.

C6. Kumar, S., Itzhak, E., **Olatunji, S.**, Sarne-Fleischmann, V., Tractinsky, N., Galit Nimrod and Yael Edan. 2019. Exploratory evaluation of politeness in human-robot interaction, *Proceedings of Quality of Interaction in Socially Assistive Robots, Quality of Interaction in Socially Assistive Robots (QISAR) Workshop International Conference on Social Robotics (ICSR'19),* Madrid, Spain, November 26-29.*

C7. Markfeld, N., **Olatunji, S.**, Gutman, D., Givati, S., Sarne-Fleischmann, V., Edan, Y. 2019. Feedback modalities for a table setting robot assistant for elder care. *Proceedings of Quality of Interaction in Socially Assistive Robots, Quality of Interaction in Socially Assistive Robots*

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(QISAR) Workshop International Conference on Social Robotics (ICSR'19), Madrid, Spain, November 26-29. Extended abstract.*

C8. **Olatunji, S.**, Potenza, A., Oron-Gilad, T., Kiselev, A., Loutfi, A., Edan, Y. 2020. Usability testing for the operation of a mobile robotic telepresence system by older adults. In *Proceedings of the 64th International Annual Meeting of the Human Factors and Ergonomics Society*, October 5-9.

C9. Markfeld, N., **Olatunji, S.**, Edan, Y. Evaluating feedback modalities in a mobile robot for telecare. Accepted to TAROS 2021 conference.[4]

Abstracts

A1. Gutman, D., Markfeld, N., **Olatunji, S.**, Sarne-Fleischmann, V., Oron-Gilad, T., Edan, Y. 2019. Evaluating fluency in robot-assisted table setting for older adults, ICR *2019 – 6th Israeli Conference of Robotics*, July 2019, Herzliya, Israel. Abstract, oral presentation. *

A2. Avioz-Sarig O., **Olatunji S.**, Sarne-Fleischmann V., Edan Y. 2019. Robotic system for physical training of older adults, *ICR 2019 – 6th Israeli Conference of Robotics*, July 2019, Herzliya, Israel. Abstract, oral presentation.*

A3. Avioz-Sarig O., **Olatunji S.**, Sarne-Fleischmann V., Edan Y. 2019. *Robotic system for physical training of older adults, Robotics: Science and Systems*, RSS 2019 - June 23, 2019 Freiburg, Germany. Extended abstract, poster presentation.*

Scientific reports submitted as part of the Horizon 2020 SOCRATES project

SR1. **Olatunji, S.,** Oron-Gilad, T., Edan, Y. September 2018. D5.1: Report from user studies on different interface designs and modalities. SOCRATES, Social Cognitive Robotics in The European Society, Grant Agreement Number 721619

SR2. **Olatunji, S.,** Oron-Gilad, T., Edan, Y. June 2019. D5.4: Report on how an interface should be designed to deal with varying LOA. SOCRATES, Social Cognitive Robotics in The European Society, Grant Agreement Number 721619

SR3. **Olatunji, S.,** Oron-Gilad, T., Edan, Y. February 2020. D5.7: Guidelines for interface design for varying levels of automation. SOCRATES, Social Cognitive Robotics in The European Society, Grant Agreement Number 721619

SR4. **Olatunji, S.,** Oron-Gilad, T., Edan, Y. October 2020. D5.9: Report on how Interaction Quality and levels of autonomy affect user experience. SOCRATES, Social Cognitive Robotics in The European Society, Grant Agreement Number 721619

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* This publication is not part of the thesis, but is included in a parallel study where I contributed to the research.

[4] This publication is not part of the thesis, but is included in a parallel study that was performed as part of the MSC thesis of Noa Markfeld where I contributed to the feedback design, experimental design, and writing.

Abstract

Rapid growth in the global population of older adults without a commensurate increase in supporting caregivers and healthcare professionals is expected to become a major societal challenge. The use of assistive robots (ARs) is a feasible solution to bridge this eldercare gap by assisting this population in daily living activities. The Covid-19 pandemic and the requirement for social isolation has increased the need for ARs to assist older adults in the case of a global crisis. However, introducing ARs to support older adults comes with inherent interaction challenges, five of which are addressed in this thesis: perceptual challenges of older adults and their particular needs, transparency in interaction, function allocation in human–robot tasks, autonomy balance between the older adults and the AR, and integrating transparency and autonomy in the interaction. This thesis (which is part of the EU Horizon 2020 SOCRATES project* on social cognitive robotics in eldercare) addresses each of these challenges to improve the interaction of older adults with ARs. Details of these interaction challenges and the thesis contributions are presented in three developmental and experimental stages.

Stage I. Bridging the automation transparency gap in ARs that support older adults

This challenge involved finding the right balance that ensures sufficient transparency (in terms of what the robot is doing, why, and what next) which is not overwhelming for the older adults, but still provides sufficient information for task completion. The solution proposed was to implement levels of transparency (LoTs), defined as the degree of information provided to the user related to the state, reasoning process, and future plans of the robot. Developing and implementing LoT models into the interaction of the users with the ARs required an applicable user-centered feedback design. This was performed by developing and evaluating user-centered feedback considering feedback content, modalities, and timing options to enhance automation transparency in different robotic platforms, tasks, and scenarios for the support of older adults. The LoT model for automation transparency was then implemented and evaluated in a robotic setup involving a mobile robot aimed to accompany the older adult and carry items as it followed the user (a person-following task).

Results from the user studies conducted in this stage, which involved 45 older adults, revealed that their preferred level of transparency was information about what the robot was currently doing. This information should be current and immediate, involving some form of friendly content such as greetings. Another study within this stage, which focused on identifying the preferred mode of feedback, revealed that voice feedback with some specific parameters that facilitated good

* http://www.socrates-project.eu/

comprehension was preferred by the participants over other forms of feedback. The study, which focused on the timing of feedback, revealed that continuous feedback with short intervals was more effective and preferred by participants over discrete and longer intervals. A final study within this stage that evaluated the effect of the aforementioned feedback design parameters on various aspects of the interaction yielded significant positive results, particularly on the engagement, understanding, and trust of the study participants. The outcome of these studies provided the design elements for incorporation of the LoT model in the later stages of development.

Stage II. Maintaining autonomy in the interaction with the ARs

This challenge involved finding the right balance of autonomy for the robot that prioritized the preference of older adults by maintaining a certain level of autonomy without diminishing the robotic assistance. Levels of automation (LOAs), defined as the degree to which the robot would carry out certain functions in its defined role of assisting the user, were developed and implemented by defining the function allocations. This was performed by identifying specific functions in the interaction based on an established function allocation model that aligned with the estimated capacities of the user and robot in the selected tasks. Suitable LOA modes (high and low modes) were then developed considering the preferences, peculiarities, and autonomy of the older adults. These modes were implemented in a robotic system to assist in a task to support older adults – a hazard perception task with a telepresence robot to perform a variety of observational tasks while identifying hazards in the home. This was evaluated through user studies with older adults and younger adults standing in as caregivers to test the robustness, reliability, and usability in different situations such as when task complexity changed.

Results from the user studies, which involved 4 older adults and 20 younger adults, revealed that the older adults were able to control the robot effectively in the developed LOA modes. They particularly enjoyed the dexterity with which the robot could be controlled in the low LOA mode, which permitted more active interaction with the AR. The objective performance results showed that they were able to complete the sub tasks successfully in both LOA modes, which highlighted the learnability and ease of use of the LOA modes. The results also revealed the potential of utilizing the robotic systems in alternative LOA modes to accomplish specific tasks or subtasks. Evaluation of the LOA modes at different levels of complexity with younger adults revealed significant interactions between the LOA modes and level of complexity. It was observed that performance improved at high LOAs when the task complexity was low. However, when the task complexity increased, lower LOAs improved performance. This opposite trend was also observed in the results for workload and situation awareness. Evaluation of the feasibility of switching between the LOA modes was also carried out to gain insight into the merits of such switching alongside the inherent switch cost implications. The usability, preference, and objective findings raised awareness towards areas of improvement in the LOA design that were useful in Stage III of the research.

Stage III. Integration of transparency and autonomy to improve engagement

Here, the challenge involved finding the right balance between engaging the older adults to avoid boredom, sedentariness, or loss of skills due to prolonged inactivity while providing sufficient information to perform the tasks that would not overwhelm or confuse them. The solution proposed was to design a framework that integrated the developed LoT and LOA models. This helped to define the degree of assistance the robot should provide for sufficient engagement with adequate feedback that ensured that the user was always kept in the loop without information overload. The model was implemented in two distinctive test cases to identify commonalities that extend beyond specific robot and task conditions: a person-following task and a table-setting task. Metrics were defined to evaluate LoT and LOA designs and combined objective and subjective metrics as a framework for evaluating the interaction.

Results from the user studies, which involved 24 older adults, revealed the importance of integrating LoT with LOA in the design of ARs supporting this population. The LoT–LOA integration proposed was successfully implemented and tested in the two test cases, providing evidence for the feasibility of the design in ARs. LoT–LOA interaction effects were found in the test cases for the aggregated metric of quality and interaction, consisting of objective and subjective metrics for engagement, fluency, understanding, comfortability, and trust. The combination of high LoT and low LOA led to increased engagement in both test cases. The significant results observed through the metrics proposed for the evaluation of the LoT–LOA design revealed the potential of using the defined metrics for further assessment of other HRI-related studies and benchmarking interaction quality. Results also revealed some task-related factors that influenced specific aspects of the interaction such as fluency, understanding, and comfortability. Some of the task-related factors highlighted were workload demands of different tasks, feedback modality conditions, and the position of the user relative to the robot. Further studies are recommended to investigate additional influencing factors. This third stage of the research combined the insights of the initial two stages to produce an empirically evaluated interaction design model with guidelines for further developments and evaluations for other ARs to support older adults.

Summary

This thesis advances interaction design in ARs that support older adults, focusing on major interaction challenges. The LoT and LOA models and LoT-LOA integration developed and evaluated in the different robotic systems point to the viability of the design and the potential for implementation in other ARs to support older adults. Findings across all studies can be summarized into the following: for a high quality of interaction, the AR should provide sufficient information on what it is doing (LoT level 1) through a feedback mode that is applicable to the specific task. Lower LOAs should be used to keep the older adult actively involved in the task. The combination of a lower LOA with a higher LoT was beneficial in maintaining the older adult's awareness of the robot's operations without overload. Yet, the specific LoT should be adapted for the specific LOA, to ensure that the robot's actions match expectations.

Keywords: Human–robot interaction, level of automation, level of transparency, assistive robots, older adults, interaction design, eldercare, interaction, interaction metrics

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List of Acronyms

ADL: Activities of daily living

ARs: Assistive robots

EADL: Extended activities of daily living

HP: Hazard-perception

HRI: Human–robot interaction

IADL: Instrumental activities of daily living

LoT: Level of Automation

LOA: Level of Automation

MBE: Management-by-Exception

MBC: Management-by-Consent

PF: Person-following

SA: Situation awareness

SAT: Situation awareness-based transparency

TS: Table-setting

Chapter 1: Introduction

1.1. Problem description

There is rapid growth in the global population of older adults due to an increase in life expectancy (United Nations, 2020). It is estimated that by 2050, one in six people worldwide will be aged 65 years or over (Allaban et al., 2020), and this population ageing trend is projected to increase (Broniatowska, 2019). This, along with a dearth of caregivers and healthcare professionals available to cater for older adults, may lead to an eldercare gap which is gradually becoming a global societal challenge (Stone, 2021). The therapeutic time devoted to each older adult is already declining and is expected to gradually diminish (Bogue, 2013), resulting in inefficient caregiving and increased hospitalizations (Chernbumroong, et al, 2013). In addition, the COVID-19 pandemic introduced isolation of this population due to the need to maintain social distancing, which has brought uncertainties to the sufficiency of health and personal care that these older adults are receiving in their homes (Sands et al., 2020).

The use of assistive robots (ARs) is gradually evolving as a viable solution to bridge the eldercare gap (Allaban et al., 2020; Tang et al., 2015; Zafrani & Nimrod, that 2019). These ARs are expected to assist older adults in three types of activities: activities of daily living (ADLs), instrumental activities of daily living (IADLs), and enhanced activities of daily living (EADLs). ADLs are basic self-maintenance tasks such as dressing, feeding and bathing. IADLs are utilitarian tasks that are not mandatory for fundamental functioning, but are essential for independent living and interaction with the environment. These include activities like housekeeping, shopping, and complying with prescribed medication. EADLs are activities that facilitate participation in social and enriching activities such as leisure time activities, pursuing hobbies, and learning new skills (McColl et al., 2013; Smarr et al., 2014). This thesis (which is part of the EU HORIZON 2020 SOCRATES project on social cognitive robotics in eldercare) focuses on five main ***interaction challenges*** as the AR carries out these activities alongside the older adult**.** These challenges are summarized in the following paragraphs.

1.1.1. Perceptual challenges of older adults

There are several age-related differences and difficulties related to the perceptual capacity of older adults (Mitzner et al., 2015). Visual and auditory capabilities are usually the most prominent factors since they present immediately obvious user capabilities and limitations in design (Czaja et al., 2019). Lack of consideration for these perceptual design differences could lead to misunderstanding or not understanding the AR's actions, reasoning, or intentions (Leite et al., 2013). It can also partially or completely limit older adults' use of it (Mitzner et al., 2015). Poor consideration of perception often leads to poor communication which inevitably affects the successful interaction of the elderly with an AR (Hellström et al., 2018). Considerations should be made for appropriate and suitable communication modes in the form of input and feedback options that can be effective in the design of ARs for older adults (Mitzner et al., 2015).

Current research has shown that ARs developed for the elderly are still lacking sufficient "sensory enrichment" (Allaban et al., 2020; Khosla et al., 2013; Portugal et al., 2019). It is important to tailor the robot's communication to fit the older adults' perceptual needs. Eldercare robots should be designed to increase usability and ensure wider user acceptance (Portugal et al., 2019). This challenge can be addressed by utilizing ***a user-needs approach in the development of a user-centered feedback design to match the perceptual capabilities and preferences of older adult users***.

1.1.2. Transparency in interaction

Previous studies revealed that transparency in interaction aids the user in maintaining that interaction (Kim et al., 2006; Lyons, 2013). The amount and rate of information presented by the robot must conform with the user's information processing capacities (Czaja et al., 2019; Eizicovits et al., 2018; Feingold-Polak et al., 2018) and relate to the environment, task, and robot (Lyons, 2013). Too little information may not be sufficient for reliable interaction with the elderly, whereas too much information can cause confusion and error (En & Lan, 2011; Grice, 1989; Lyons, 2013). A balance that ensures sufficient transparency that is not overwhelming, yet provides sufficient information is still lacking in the majority of AR designs, particularly in the eldercare domain (Allaban et al., 2020; Czaja et al., 2019).

This challenge can be addressed by ***adapting levels of transparency (LoTs) into the interaction of users with ARs through user-centered feedback***. LoT is the degree of information provided to the user related to the state, reasoning process, and future (projected) plans of the system (Chen et al., 2014). Defining suitable LoTs for an interaction requires factoring the necessary elements of interaction into the ***transparency model that ensures that information presented by the AR considers the differences and challenges in the cognitive processing capacities of older adults***. This is to support these users in perceiving the elements in the interaction, comprehending these elements, and considering the potential implications of these elements in future actions (Chapter 3).

1.1.3. Function allocation in the development of ARs to support older adults

Function allocation is aimed to ensure that tasks (and subtasks) in the system are appropriately allocated to the human, robot, or both (Lee et al., 1992). Previous research examined the allocation of roles based on estimated capacities of the human and machine in a given situation to ensure effective human–machine interactions (Dekker et al., 2002). Some studies identified social roles for adaptive interaction of ARs with users (Allaban et al., 2020; Fiorini et al., 2019; Frennert et al., 2020;

Huber et al., 2014; Kachouie et al., 2017; Mitzner et al., 2014; Rossi et al., 2018; Smarr et al., 2012). However, these studies were mostly qualitative in nature. Various categories of users were interviewed regarding their perception on potential roles ARs could fill, while supporting them with 18 activities of daily living. Studies with actual implementation and evaluation of these roles in utilitarian tasks in the home considering the basic stages of function allocation are very limited.

This thesis addresses the above gap by identifying functions involved in the interaction for specific tasks – ***at different stages of the interaction.*** These functions are then allocated in roles matching current capabilities of the ARs and the older adults. This provides a structure to preserve the autonomy of the users in the interaction as the ARs support them in their daily activities (Chapter 4).

1.1.4. Autonomy in the interaction

The preference of most older adults is to maintain a certain level of autonomy as they perform their daily living tasks (Smarr et al., 2012). This independence in living is a pertinent factor to consider and should not diminish when introducing robotic assistance (Smarr et al., 2012). This is important to consider to avoid misinterpretation of user–robot roles in the interaction. Misinterpretation of roles could potentially result in a mismatch of expectations where there is a lack of fit between user expectations of the robot's role during caregiving and the robot's actual performance (Doisy et al., 2014; Flemisch et al., 2012). A mismatch could further lead to misuse – if the older adults over-rely on the robot or disuse it, or if they under-utilize it (Parasuraman et al., 1997). In an eldercare setting, such consequences can significantly degrade the quality of user–robot interactions.

A strategy proposed in the literature to address this mismatch is through levels of automation (LOAs), which can be explained as the degree to which a robot would carry out certain functions in its defined role of assisting the user (Beer et al., 2014; Endsley et al., 1999). Previous studies have shown that the possibility of adjusting the robot's involvement in these tasks can help facilitate their use (Kaber, 2018). In the context of robot-assisted eldercare, it is important to accommodate the autonomy of different users and successfully manage a variety of situations and tasks without compromising the quality of the interaction (Flemisch et al., 2012). This thesis proposes ***level of automation models suitable for ARs supporting older adults in specific utilitarian tasks***. These models were tested under different conditions to evaluate their suitability and influence in the interactions (Chapter 4).

1.1.5. Integrating transparency and autonomy to improve engagement in interaction

It is imperative that older adults be sufficiently engaged physically, cognitively, and socially in agreement with the goals of active and successful aging (Rowe and Kahn 1987).Therefore, interacting with an AR should engage their physical and mental capacities so as not to cause boredom, which could lead to sedentariness and loss of skills connected with daily living due to prolonged inactivity

(Beer et al., 2014). A reliable design that will adequately engage older adults should meet their needs and preferences, while keeping them informed of the robot's actions, capabilities, and limitations (Parasuraman et al., 2008). This is related to the degree of information provided to the users (LoTs) and their degree of involvement in the operation of the AR (LOAs). Appropriately combining these two variables in the interaction is a design challenge that has not been critically addressed in previous research, which may have partially or completely limited use of these ARs by the elderly.

This thesis ***proposes a design framework that integrates developed level of transparency (LoT) models with level of automation (LOA) models***. This helps to define the degree of assistance that the robot should provide for sufficient engagement with adequate feedback that ensures that an older user is always kept in the loop without an overload of information. The effect of this on the interaction of older adults with the robot was explored in different tasks and through various interaction variables to test the model (Chapter 5). Metrics to evaluate the LoT and LOA design combinations were also defined and evaluated through user studies, aiming to ***provide a holistic framework for evaluation***.

1.2. Research objectives

The main objectives of this research were to develop robotic applications and empirically evaluate:

1. Level of transparency (LoT) models in ARs that support older adults.
2. Level of automation (LOA) models in ARs that support older adults.
3. A model to integrate LoT and LOA to improve the user–robot interaction for older adults.

The research is implemented by developing and evaluating a set of test cases with older adults focusing on instrumental activities of daily living (IADLs). The specific use cases selected were: a **person-following** (PF) task with a mobile robot, aimed to accompany the older adult and carry items as it followed them; a **table-setting** (TS) task with a robotic manipulator to set eating utensils on a table in preparation for a meal; and a **hazard perception (HP)** task with a telepresence robot to perform a variety of observational tasks, while identifying hazards in the home. Additional use cases were performed as part of parallel studies and included a **table-clearing** task with the same robot manipulator as the TS and a **physical training** task with humanoid robots. The commonality in all use cases was the application of the LoT-LOA model.

1.3. Research contributions and innovation

This thesis advances interaction design in ARs that support older adults, focusing on aspects related to transparency and feedback design (LoT), function allocation and LOA design, and their integration. To accomplish this, real robotic implementations were developed and evaluated empirically in three use cases that provided the ability to look at the integration of LoT and LOA beyond one specific use case and identify commonalities and needs of older adults in ARs. Innovations are:

- Implementing an LoT model for assistive robots (ARs) that support older adults

- Developing a LOA model for ARs that support older adults
- Integrating LoT and LOA models in ARs that support older adults
- Identifying commonalities and generalities across use cases and tasks with ARs that support older adults

Test cases that included three different robots and tasks were specially developed, and user studies were performed with a total of 73 older adults aged 62–91 (M=78, SD=5.8).

1.3.1. Automation transparency for ARs interacting with older adults

Some studies have evaluated feedback modes for ARs supporting older adults in the areas of physical support (Fischinger et al., 2016; Gross et al., 2017), rehabilitation (Ye et al., 2012), social interaction (Goetze et al., 2012; Rehrl et al., 2012), cognitive support (Góngora et al., 2019; Gross et al., 2017), safety monitoring (Hall et al., 2019; Kuo et al., 2013), information support (Woo et al., 2012), emergency services (Goetze et al., 2012; Rehrl et al., 2012), and rehabilitation (Ye et al., 2012). Specific applications include table setting and meal assistance (Markfeld et al., 2019; Ms et al., 2012), and physical exercise motivation and training (Avioz-Sarig et al., 2020; Fasola et al., 2013). However, none of these studies evaluated transparency-related feedback content in relation to other feedback aspects such as the mode and timing of the feedback.

This thesis contributes to the existing body of knowledge by:

- Developing and evaluating user-centered feedback considering feedback content, modalities, and timing options to enhance automation transparency in different robotic platforms, tasks, and scenarios supporting older adults.
- Adopting a suitable model of automation transparency in ARs supporting older adults that accommodates the differences and challenges peculiar to the population.
- Identifying different levels of transparency (LoTs) applicable for older adults' interaction with ARs to ensure adequate situation awareness without confusion.
- Implementing the required transparency in different robotic setups, tasks, and situations that matches the needs of the users.

1.3.2. Developing LOA models suited for robot-assisted tasks to support older adults

LOA models and their evaluation have been implemented with expert and non-expert users in many test cases for different tasks including avionics (Parasuraman, 2000), computer-based control tasks (Endsley et al., 1999), automated driving and simulations (Endsley et al., 1995), manufacturing (Draper, 1995), unmanned aerial vehicle control (Hocraffer et al., 2017), agriculture (Berenstein et al., 2017), underseas teleoperation (Sheridan, 1992), rehabilitation (Jipp, 2014), and various forms of simulations (Kaber et al., 2000). While there are rare LOA models incorporated in robots for older adults, and some form of automation change has been implemented in some rehabilitation devices (Jipp, 2014; Soyama et al., 2004), to the best of our knowledge, LOA models suited for elder care tasks have not been critically evaluated. As aforementioned, older adults' preferences must be taken into account, along with their varying characteristics. It is important to create engagement with minimal workload and a user-friendly awareness of robot operations without information overload. Autonomy of elderly users is also expected to be considered in the automation for carrying out daily chores and hobbies, while adequately addressing the necessary ethical concerns (Allaban et al., 2020). Evaluating developed LOA models should be addressed. This thesis contributes by:

- Identifying specific functions in the interaction based on an established function allocation model to define the roles of the robots and older adults in selected utilitarian tasks. These functions are allocated based on estimated capacities of the user and robot in a given situation to ensure coordination and collaboration between the human and automation of the robot.
- Developing models that consider preferences, peculiarities, and autonomy of older adult users
- Implementing these models in three different assistive robot tasks to support older adults.
- Evaluation of these models through user studies to test their robustness, reliability, and usability in different situations.

1.3.3. Integrating LoT and LOA models

Examining how levels of transparency (LoTs) and automation (LOAs) affect interaction design considerations for robots supporting older adults in everyday tasks is critical in promoting successful interaction and acceptance of these ARs. This has not been examined previously in research focusing on ARs supporting older adults. Recommendations regarding the importance of designing autonomy into robots, along with defined levels of transparency have been made (Hellström et al., 2018; Kim et al., 2006; Wortham, 2020; Wortham et al., 2017). However, no model has been developed that integrates the AR automation with the specific levels of transparency and evaluated the effects in user studies. Thus, this thesis contributes by:

- Developing a model for integrating LoTs and LOAs to match the preferences and expectations of older adults.
- Implementing the model in distinctive test cases developed to identify commonalities that extend beyond specific robot and task conditions
- Defining metrics to evaluate LoT and LOA designs that combine objective and subjective metrics to provide a framework for evaluating the interactions. Evaluation frameworks are desperately needed for HRI evaluations.
- Providing insights and recommendations for interaction design considerations in ARs focused on elder care.

1.4. Thesis structure

The thesis is structured as follows: Chapter 2 provides the methodology detailing the framework elements, theoretical framework, design, and development. It also includes an overview of the experiments, test cases, and participants. Chapters 3–5 detail each of the framework modules, the designs made, and experimental evaluations of the designs. Each chapter is independent, providing an overview, methods, results, and conclusions for each module developed to achieve the objectives. Chapter 6 gives a summary of the results from the publications that constitute the different stages of the research. Chapter 7 presents a general discussion on the main aspects investigated. Finally, Chapter 8 presents the main conclusions from each module development and provides recommendations for interaction design ARs supporting older adults, as well as for future work.

Chapter 2: Methodology

2.1. Framework elements

The section presents the component elements in the overall interaction of the older adults with the AR (Figure 1). The research connected with LoTs included sequential and parallel studies to yield suitable feedback parameters to facilitate automation transparency. The research involving LOAs spans across studies to define the roles and functions of the ARs as they support the test population. These were carried out by designing and assigning different LOA modes applicable to ARs supporting older adults, while ensuring adequate transparency (LoTs) through various feedback modalities. The factors that contribute to interaction quality as older adults interact with the ARs were also evaluated: human variables (such as peculiarities of the older population), robot variables (such as differences in robot types), task variables (such as various activities of daily living), and environmental variables (such as characteristics of the physical environment). These factors were assessed through user studies involving various platforms, use case scenarios, and setups.

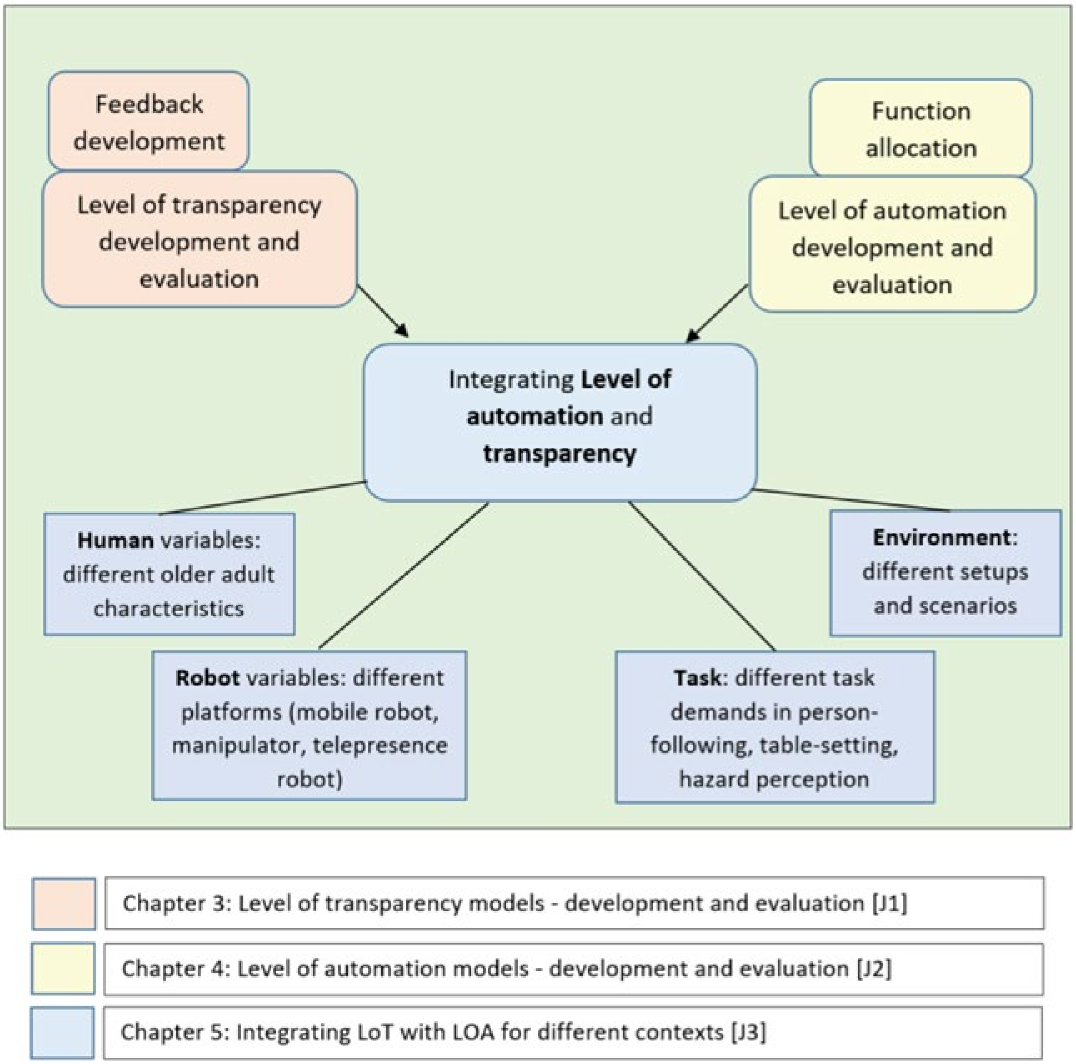

Figure 1: Interaction design framework for the various interaction design modules

LoT defines the content of this information to and from the user. LOA delineates the role and actions expected of the robot in the interaction. This requires information exchange between the robot and the user in the form of instructions and feedback. These elements are put together through an interface that is modelled as a shared task interface. The details of the elements involved in the design of the LoT models, LOA models, and the integrated model are presented as follows:

2.1.1. User-centered feedback to evaluate elements for the LoT and LOA modes

The necessary elements for the feedback through which the user would interact with the AR were collected through a coactive design perspective. It involved preliminary discussions with older people on their expectations about a robot in the context of person-following. This aligned the thoughts of the potential users and designers into the same conceptual design zone, ensuring that the robot performance was tuned to meet the users' expectations. The highlights of these preliminary discussions bordered on the overarching goals of the robot such as what the robot does, why, and how. This laid the foundation for the incorporation of the model of transparency and automation in the subsequent studies.

Preliminary experiments were then conducted to explore feasible feedback design options in different conditions for person-following and table-setting tasks (Olatunji et al., 2019; Olatunji et al., 2018). These preliminary experiments provided some environment-related preferences, constraints, and context that provided inputs for the user-centered feedback design studies. These studies were a set of sequential user studies conducted with older adults to evaluate the preferred:

- Level of robot transparency and the desired content for the feedback.
- Mode of feedback.
- Timing of feedback.

Other studies through which these feedback design parameters were assessed included interaction with an AR in a physical training task (Avioz-Sarig, 2019; Avioz-Sarig et al., 2020), a table-setting task (Markfeld, 2020; Markfeld et al., 2019), a table clearing task (Gutman, 2020; Gutman et al., 2020), and a telecare task (Markfeld et al., 2020). These studies were performed in parallel to this thesis. Insights from them highlight the merits of voice feedback combined with visual feedback as the preferred feedback mode where applicable. The studies also pointed to the effectiveness of continuous feedback over discrete feedback to keep users constantly aware of the state of the interaction. The outcome of these studies regarding various feedback parameters evaluated in different contexts and situations provided some inputs used in the design guidelines for the integration of LoTs with LOAs in the interaction design.

2.1.2. Design of the LoT Modes

The aim of the LoT design was to provide as much information as needed to the user at every point in time without overloading them. The design is modelled using the Situation Awareness-based Transparency model (SAT) with the following levels (Chen et al., 2014): *Purpose and perception* – the LoT which provides information on the current state of environment, task, robot, human, or interaction; *Comprehension and reasoning* – the LoT that defines how the state of the environment, task, robot, human, or interaction may affect the users' interaction with the robot; and *Projection and prediction* – the LoT that gives information on the next state in the interaction based on the present status and other intervening factors. During the interaction, the following five information classes were provided to the user:

1. Task-related information: information from the robot to the user regarding its state or its actions, as connected with the task at hand. It includes details of the task such as time required for completion, constraints connected to the task, demands and dependencies in the task, requirements for the task, and progress in the task (Chen et al., 2014; Endsley, 1995; Hoffman, 2019b).
2. Environment-related information: the type of environment (e.g., indoors, outdoors, corridor, open space), conditions prevalent in the environment (e.g., illumination conditions, clutter, obstacles, weather conditions), environmental constraints, and safety-related environmental information (Adamides et al., 2017; Honig et al., 2018; Lyons, 2013; Wachs et al., 2007).
3. Robot-related information: information pertaining to the operation and behaviour of the robot i.e., the degree of reliability of the robot, principles underlying its decision making and all other tasks (e.g., information on how to use a specific feature of the robot or on the battery charge level of the robot) (Jevtić et al., 2015; Theodorou et al., 2017).
4. Human-related information: the human's physical condition (e.g., heart rate, tiredness), cognitive state (e.g., engrossed, confused), emotional state or mood (e.g., happiness, fear). It also includes information regarding the workload or stress the human is experiencing (Inagaki, 2008).
5. Interaction-related information: details of the human and robot's roles in the interaction, shared awareness, and dynamics of the teamwork (Inagaki, 2008). It entails information of how subtasks are allocated as the roles in the LOA condition being used and how each role will be executed.

Research on users' LoT preferences regarding the four classes of information (task, environment, robot, human) revealed that older adults preferred the purpose and perception transparency level for these different classes (Olatunji et al., 2020). Most older adults wanted the robot to be current and immediate, providing only status information. In some situations, they asked for a higher level of transparency to know why the robot took certain actions (comprehension and reasoning). In fewer cases, out of curiosity, they asked to know what the robot planned to do next (projection and prediction). Based on Theodorou et al. (2017), and also our study conducted regarding transparency in feedback (Olatunji et al., 2020), the amount of information for each class of information was designed into the LoT modes set as follows (Figure 2):

- Low LoT mode: the robot presents status information regarding environment, task, robot, and user. It also presents additional information to support the interaction in certain cases (e.g., if something is not functioning as expected).
- High LoT mode: the robot presents status information regarding environment, projects the next stage in the task, gives reasons for its actions, and presents how information about the user could affect its actions and the future state of the interaction.

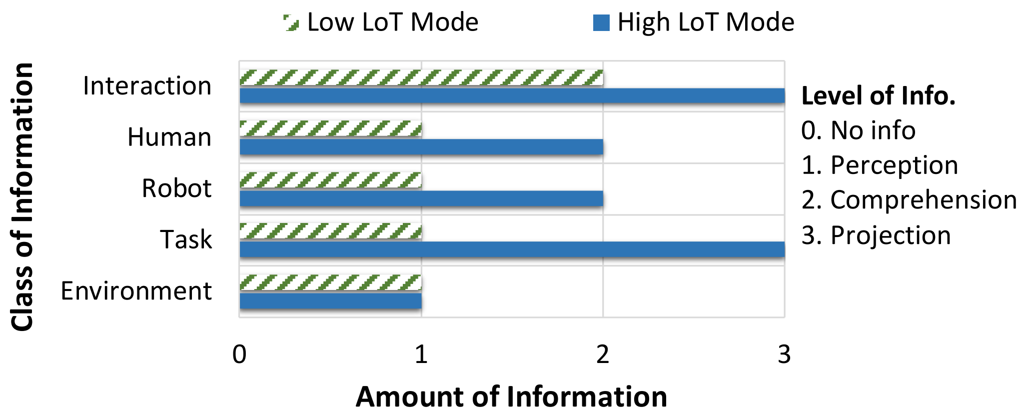

Figure 2: The LoT conditions developed for the experimental test cases. These are described in terms of the class and amount of information the AR provides. In the High LoT, the AR provides more predictions about all classes of information. In the Low LoT, only basic status information is given.

2.1.3 Design of the LOA Modes

A major consideration in designing the LOA mode was to keep the older adult involved in the task while controlling the robot. The LOA design can be modelled by the four stages of information processing (Parasuraman et al., 2000) denoted as the OODA loop (Brehmer, 2005): acquiring information (Observe), processing information (Orient), making decisions (Decide), and taking action (Act): *acquiring information* involves gathering it before performing the task, *processing information* requires generating options for performing the task, *making decisions* entails identifying which of the options to select in performing the task, and *taking action* encompasses all steps associated with the decision made.

Four levels of automation were carefully weighed based on human–automation system design guidelines and recommendations (Beer et al., 2014): Robot alone, in which the robot performs all actions without any form of human involvement; Robot-Oriented Semi-Autonomy (MBE), in which the robot implements actions unless the user objects, and informs the user of the implemented action following its execution; Human-Oriented Semi-Autonomy (MBC), in which the user must explicitly agree to suggested actions before they are performed by the robot; and Human alone, in which the robot is not involved in any part of the task. The human performs all actions.

To encompass the four levels at different phases of the OODA loop, two LOA modes were designed to ensure: a) that the human is always kept in the loop, regardless of the automation level, and b) that the robot always helps the human, but as little as possible, so human skills are maintained and sedentary behaviour is avoided. The specific LOA combinations within the OODA loop components define the following two tested LOA modes (see Figure 3).

- Low LOA mode: the robot minimally assists the human in acquiring information related to the task by presenting information through the applicable interface. The robot also assists in information processing by providing options through which the task could be performed. The human must agree to the suggestions before the operation can continue. The human then solely makes the decision regarding what should be done, while the robot assists in the execution of the actions.
- High LOA mode: the robot is more involved than the human in acquiring information regarding details of the task. This information is fully processed by the robot. All decisions related to the task are made only by the robot. The robot executes the decision, but can be interrupted by the human.

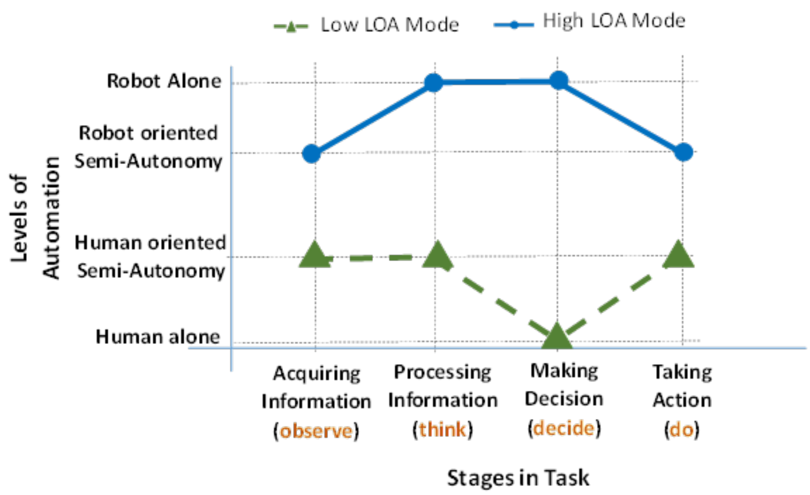

Figure 3: LOA modes designed for older adults' interaction with ARs. The tested LOA modes are described as an Observe–Orient–Decide–Act (OODA) loop. In the High LOA mode, decisions are made by the AR, and the human can overrule them upon execution. In the Low LOA mode, the human makes the decision alone.

2.1.4 Integrating LoT and LOA

A schematic model for integrating LoT and LOA settings in a user interface through which information quantity (LoTs) and robot involvement (LOAs) can be adjusted for the task proposed (see Figure 4).

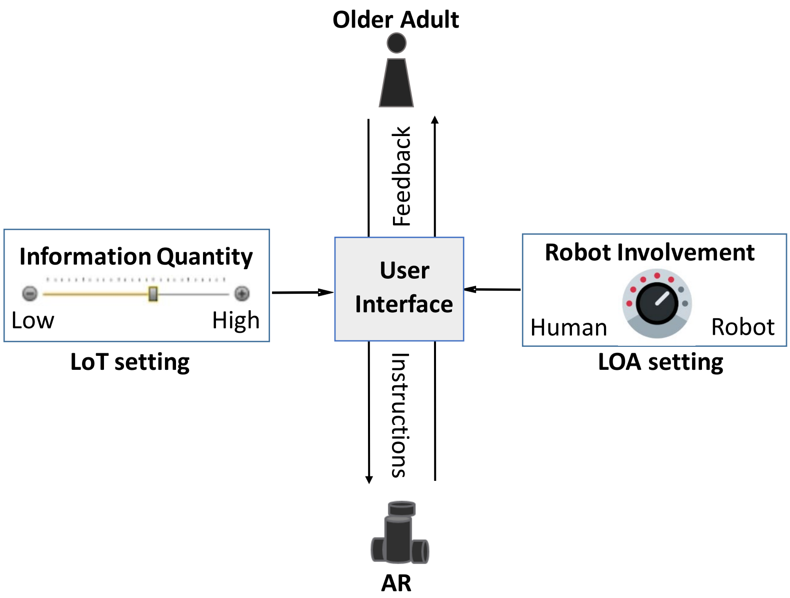

Figure 4: A schematic model for integrating LoTs and LOAs for interaction design of ARs for older adults.

The model is adapted for each test case using a designated interface considering ecological interface design principles (Vicente et al., 1992). Significant interaction between LoTs and LOAs is expected, as lower levels of automation require more involvement of the user and more information (Olson et al., 2001). The feedback parameters through which the information exchange occurs is considered in the user interface design, as gathered through the user studies conducted (Section 2.1.1).

2.2. Experimental use cases and tasks

Preliminary consultations were held with older adults (end-users) groups where possibilities for the assistive roles and functions of the robots were discussed. The older adults suggested various kinds of tasks they would like the robot to assist with. The thesis targeted utilitarian tasks for older adults. The outcome of these consultations was different preferences and expectations of the older adults regarding tasks the robot could support with. Tasks that could match the technological capabilities of the robots were then considered, along with feasible developments that could be made within the timeline for the research. These led to the user cases and tasks selected which are presented as follows:

2.2.1. Person-following

This task required the participant to walk a designated path to retrieve an item placed at a distance from them with a mobile AR following autonomously from behind. The participant was expected to place the item on the robot after retrieving it and return to the start position for each of the experimental conditions (Figure 5).

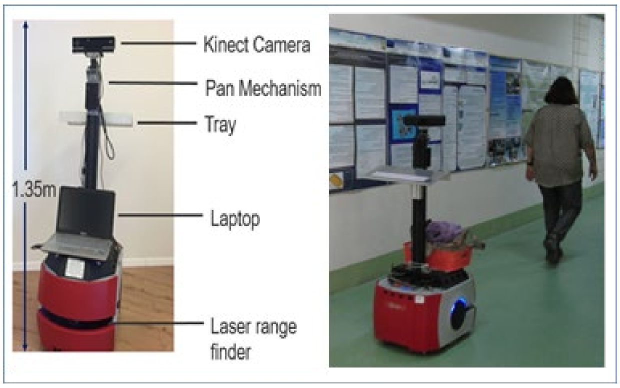

Figure 5: Left, the person-following robot platform.
Right, the experimental setup with the robot following the user along a corridor.

2.2.2. Hazard perception

This task was to navigate a telepresence robot remotely located in a home-like setup (Figure 6). While navigating the robots to different parts of the home, the user was expected to carry out some subtasks related to hazard perception in the home such as checking if there were any fall-risk items lying on the floor along the way (e.g., a loose hanging cable on the floor).

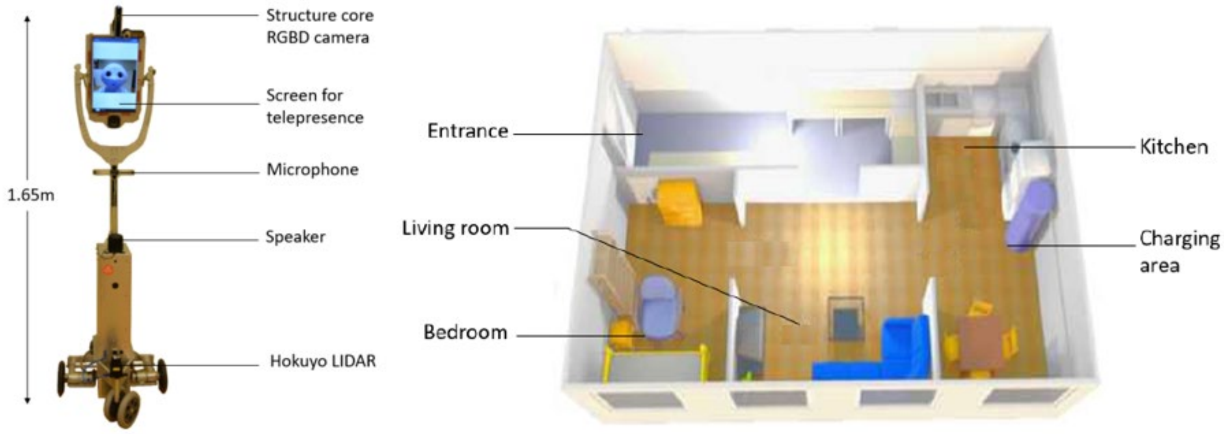

Figure 6: Left, Telepresence robotic platform used for the study.
Right, Home-like environment used for the study.

2.2.3. Table-setting

In the table-setting task, the user sat at a table where a robotic arm was located. The robotic arm placed on a table in front of the user a plate, fork, knife, and cup at specific positions in preparation for a meal (Figure 7).

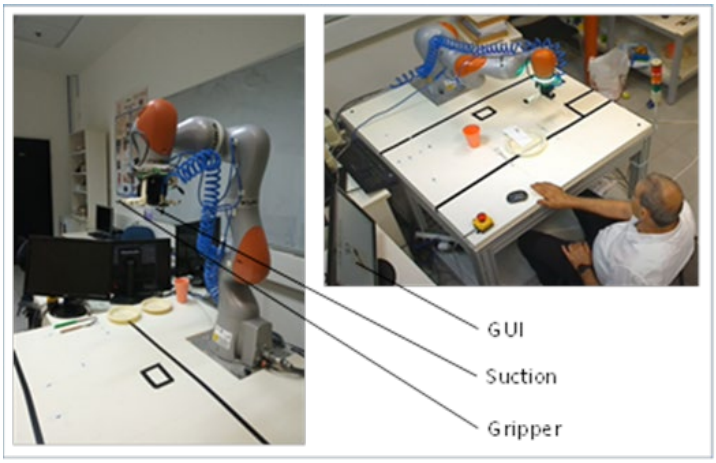

Figure 7: Left, Table-setting robot platform and experimental setup.
Right, a participant instructing the robot via the screen to the left of the user.

2.3. Overview of experimental stages and studies

The research was conducted in three main stages (Table 1), with different studies to evaluate the LoT, LOA, and LoT-LOA integrated models in different tasks using different robotic platforms as the older adults interacted with the ARs. The studies in each stage were performed sequentially such that findings in one study provided design inputs for the subsequent study. The older adults were recruited through snowball sampling, social networks and colleagues. They were mostly healthy adults with no major disability. Their educational, technical and occupational background as well as their general attitude to technology and robots are provided in the individual studies in each stage.

Table 1: Main stages and studies

Stages	Studies	Independent variable(s)	Use cases and tasks	Robot platform	Population	Thesis chapter and reference
Stage I LoT development	Study 1	Level of transparency and content of feedback	Person-following	Pioneer LX robot	45 older adults (aged 62–91, *M=78, SD=5.8*)	Three (J1)
	Study 2	Mode of feedback				
	Study 3	Timing of feedback				
	Study 4	Implemented feedback				
Stage II LOA development	Study 5	LOA modes	Hazard perception	Modified Giraff telepresence robot	4 older adults (aged 66–71, *M=68, SD=2.2*) and 20 young adults	Four (C8, J2)
	Study 6	LOA modes and task complexity				
Stage III LoT-LOA integration	Study 7	LoT and LOA modes	Person-following Table-setting	Pioneer LX robot KUKA robot	24 older adults (aged 62–85, (*M=75.4, SD=5.8*)	Five (J3)

2.4. Stages of the research

2.4.1. Stage I – LoT Development

The LoT design included four studies with 45 older adults (aged 62–91, M=78, SD=5.8) that provided a user-centered feedback design to ensure that the design focused on users' needs and preferences. The first three studies explored the older adults' preferences regarding feedback parameters (content of feedback, level of transparency, mode and timing of feedback) for a person-following robot. The preferred feedback parameters were then implemented and evaluated in a final experiment to evaluate the effectiveness of the design. The outcome of the studies provided LoT design elements which were used in the integration of LoTs with LOAs in Stage III.

2.4.2. Stage II – LOA Development

This stage focused on developing the LOA modes and evaluating these modes in user studies. It consisted of two studies involving 4 older adults (1 female, 3 males), aged 66–71 (M=68, SD=2.2) and 20 younger adults (7 females, 13 males) who participated as potential caregivers. Two LOA modes were developed and implemented in a telepresence robot. The first study was for usability testing aimed to evaluate these LOA modes in a telepresence robot controlled by the older adults. Participants navigated the robot to locations in the home, e.g., to check if the front door was closed. The second user study which involved a similar task further tested the LOA modes at different levels of task complexity. The outcome of the study revealed usability potentials of the LOA modes implemented, as well as insights for further evaluation of the integration of LoTs and LOAs in Stage III.

2.4.3. Stage III – LoT-LOA Integration

This stage drew insights from Stages I and II in the integration of LoTs and LOAs to match the preferences and expectations of the study population. The aim was to examine whether there were commonalities in LoT and LOA design implementations beyond a specific robot and task conditions. Metrics were also defined to evaluate LoT and LOA design combinations. The integrated design was tested in two distinctive test cases (a person-following task with a mobile robot and a table-setting task with a robot manipulator) with 24 older adults (14 females, 10 males); aged 62–85 (M=75.4, SD=5.8). The study revealed the importance of integrating LoTs with LOAs in the design of ARs supporting older adults. It provided evidence for the feasibility and viability of the interaction design in ARs, and yielded design guidelines for designs in ARs for older adults. It also revealed the potential of using the defined metrics for further assessment of other HRI-related studies.

2.5. Metrics for interaction design

The metrics defined to evaluate the integrated model included objective and subjective assessments of engagement, fluency, comfortability, understanding, and trust as detailed below:

Engagement captures the details involved in initiating a connection between the human and the robot, maintaining that connection, and regulating it till the end of the interaction (Robins et al., 2005). Objective metrics include gaze duration of the users as they focus on the robot or graphical user interface (GUI) of the robot and the number of user-initiated voice and gesture responses in the interaction. Subjective metrics are assessed through questionnaires related to the attention given to the robot or GUI (using adaptations from the engagement perception for social robots, and attention dimension in Corrigan et al. (2016)).

Fluency is the coordination of the shared task between the human and the robot for successful synchronization of plans and actions (Hoffman, 2019a). It can be measured objectively through task duration of concurrent activity, human and robot idle time, or functional delay in the interaction. Subjective metrics are assessed through questionnaires on the timing of the robot's actions and feedback during the interaction (a subset of the Human–Robot Fluency Scale in Hoffman (2019a).

Understanding is the accurate comprehension of details of the interaction to promote a successful interaction of the human with the robot (Hellström et al., 2018). It can be measured objectively through the number of clarifications made by the participant to the experimenter regarding the information the robot is providing. Another objective metric is the participant's reaction time while interacting with the robot. Subjective metrics are assessed through questionnaires on the comprehension of the robot's actions, and information it provides during the interaction [understanding dimension of the Situation Awareness Rating Technique in Taylor (2017)].

Comfortability is the extent to which the human experiences ease, absence of stress, or pain or other forms of discomfort resulting from the interaction with the robot (Wang et al., 2019). It can be measured objectively through physiological signals connected with stress, fatigue, or relaxation such as heart rate difference measurements. Eye movements (Wang et al., 2019) observed in gaze shifting to monitor the robot's actions during the interaction can also indicate some degree of discomfort or lack of ease. Subjective metrics are assessed through questionnaires that relate to the ease of interaction with the robot, and the extent of stress experienced during the interaction [a subset of the Robotic Social Attributes Scale Carpinella et al. (2017)].

Trust is the disposition to rely upon the abilities or capabilities of the robot based on a certain degree of satisfaction in the level of performance (Xu et al., 2016). It can be measured objectively in terms of proximity to the robot and in other actions reflecting degrees of dependence on the robot. Subjective metrics are assessed by questionnaires that relate to the extent of dependence on the robot and perceptions of mistakes the robot makes [a subset of the Human–Robot Trust Scale (Schaefer, 2013)].

Chapter 3: Level of transparency in interaction design

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Research Article Open Access

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User-centered feedback design in person-following robots for older adults

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Abstract: Feedback design is an important aspect in person-following robots for older adults. This paper presents a user-centered design approach to ensure the design is focused on users' needs and preferences. A sequence of user studies with a total of 35 older adults (aged 62 years and older) was conducted to explore their preferences regarding feedback parameters for a socially assistive person-following robot. The preferred level of robot transparency and the desired content for the feedback was first explored. This was followed by an assessment of the preferred mode and timing of feedback. The chosen feedback parameters were then implemented and evaluated in a final experiment to evaluate the effectiveness of the design. Results revealed that older adults preferred to receive only basic status information. They preferred voice feedback over tone, and at a continuous rate to keep them constantly aware of the state and actions of the robot. The outcome of the study is a further step towards feedback design guidelines that could improve interaction quality in person-following robots for older adults.

Keywords: feedback design, person-following, socially assistive robots, human-robot interaction

1 Introduction

Socially assistive robots (SARs) are being developed to assist older adults in a wide range of activities. A major effort is focused on instrumental activities of daily living (IADLs), tasks that are not mandatory for fundamental functioning but essential for independent living and interaction with the environment (e.g., activities like housekeeping, or shopping) [1]. Some of these activities can be made easier for older adults with the assistance of a person-following robot. The robot can be programmed to autonomously track the older adult and follow as he or she moves while providing assistance. It often has a compartment to carry the belongings of the user as it follows. This relieves the older adults from the physical stress of carrying loads while walking and performing other IADLs [2]. The robot can also serve the purpose of safety monitoring and companionship whilst supporting the older adult to maintain their independence in the home and outside.

Person-following is an important aspect in many service robotic applications [3] but it should be designed to conform with social norms and cultural values in order to inspire confidence and acceptability in the users. To create robots that move in socially acceptable manners, it is important to consider a multitude of parameters. These parameters include the robots' speed, acceleration and deceleration properties, the lead human's walking speed, and the appropriate physical proximity, as a function of the environment (e.g., a narrow corridor vs. an open room), the context (e.g., routine vs. urgent), and the user's physical state and intentions [2, 4, 5]. In addition to the robot's movement, there are other crucial components in the user's interaction with the robot that can affect the quality of the interaction (QoI) [6].

Identifying and addressing these crucial components require user studies to improve and ensure smoother human-robot interactions in person-following robots [7]. This is particularly critical for older adults who have peculiar needs that require attention [8, 9]. Some of these needs could be perception-related such as decline in visual, audial and haptic acuity [10]. Needs are also related to cognitive challenges that affect the rate of understanding, integrating and processing of information [11]. Physical challenges connected with stability and movement limitations also require special consideration during design [9]. SARs designed for older adults must therefore cater for their needs to ensure that the age-related peculiarities do not partially or completely limit their use.

The current paper utilizes this user-needs approach in the development of a user-centered feedback design for a person-following robot that matches the perceptual

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capabilities and preferences of the potential users (older adults). The paper also reveals the positive influence such user-centered approach has on various aspects of interaction between the older adults and the robot.

2 Related work

Successful interaction requires communication between the human and the robot which generally involves sending and receiving of information to achieve specific goals [12]. Communicative actions when presented in the most comprehensible form promote understanding which aids a successful interaction of the user with the robot [13–16]. The communicative actions from the robot to the user, herein referred to as feedback, are the presentation of information by the robot to the user in response to user's actions.

The content of the feedback information provided is an essential influencing factor for successful interaction between humans and robots [17]. Feedback content is predicated on the desired level of transparency (LOT) [18, 19]. LOT, in this context, can be described as the degree of task, environment, robot, human, and interaction-related information provided to users while the robot is performing its task [20].

Task-related information consists of information provided by the robot to inform the user of its state, or its actions in relation to the task. It also includes information on the reasons for actions taken while executing the task, the next actions to be taken and the progress of the task. This was demonstrated in the situation awareness based transparency model (SAT) for autonomous systems developed by Chen et al. [21] which mirrors Endsley's model of situation awareness [22]. An adaptation of that model in relation to a person-following robot is presented in Table 1.

Environment-related information which the robot could provide include constraints of the environment, type of environment and any other safety-related information about the environment [5, 20, 23]. Robot-related information includes information from the robot regarding its degree of reliability, underlying principles of its decision making and all other information pertaining to the robot (for example, information on battery status, operating mode, how to use a specific feature on the robot etc) [24].

Human-related information includes the human's physical and emotional state if the robot can assess it. It also includes information regarding the human's effort in the task, workload or stress encountered if it can be provided by the robot [25]. Interaction-related information involves details of the roles of the robot and human in the interaction, shared awareness and dynamics of the teamwork [25, 26].

Implications of providing information to users was explored in [27]. They suggested that a robot which is truly transparent may contravene the ideology of worthy companionship where the companion has a social value of independence, agency and autonomy to disclose information. The authors hypothesized that as transparency is increased, the user may perceive the robot more as a tool than a companion. This is contrary to the expectation desired in domestic and healthcare settings where the users are expected to interact with the robots as partners, companions and entities capable of caring for them. It was recommended that various levels of transparency in the robot's communication should be evaluated in a wide range of domestic environments to explore the relationship between transparency, utility and trust for HRI [27].

How the robot communicates is also a crucial component of the interaction in relation to what information is being communicated [27–29]. The information can be presented in various modes such as audial, visual or haptic modes [11, 30]. It could also be in various other forms of non-verbal modes such as eye blinks, shifts in gaze (for robots with a face) or body posture for humanoid robots [31]. Implicit non-verbal communication positively impacts understandability, efficiency and robustness to errors arising from miscommunication [31]. Transparency often helps to reduce the conflict in joint task situations when such errors occur [31]. The effect of transparency and communication modality on trust was examined in [32]. The modality was not significant in the study which included a simulated robot deployed on a desktop computer, though the transparency manipulation was significant. This interaction differs from interaction with a mobile and embodied robot such as a person-following robot which this current paper focuses on. Also, the users in [32] were undergraduate students (aged 18-22) which have different characteristics and perceptual peculiarities from the older adults. It was recommended that more user studies should be carried out in specific domains in order to determine influence of information level, modality and content on trust.

When discussing strategies to foster transparency between the human and the robot, it was recommended that the interface through which the human interacted with the robot should provide useful information relating to the task and environment [20]. The author cautioned that too much information or a non-intuitive display may cause confusion or frustration for the user [20]. This is in

Table 1: Information provided at various LOT.

LOT	Information provided
1. Perception	Information about the state of the robot and/or contextual information that the user must be aware of. For example – the robot makes a sound or says 'yes' when it acknowledges the user giving a command
2. Comprehension	Information about how the state of the robot or the context may affect achieving the goal. For example – the robot verbally says that it is following the user from behind in a distance of 2 meters
3. Projection	Information about how the future state of the robot may change based on the context. For example – the robot verbally says that in a few meters it will have to slow down due to an obstacle ahead

agreement with the findings in [33] where it was additionally noted that multi-modal communication aided performance of the users. Though Kim and Hinds [34] remarked in their study that users understand the robot better if it explains the reasons behind it's behavior. This was confirmed by [35] in an unmanned aerial system scenario with multiple operators. It was recommended that the hypothesis should be further investigated in other scenarios to determine if the findings vary with the complexity and nature of the task or environment. Studies conducted in [20] added that cues to signify what the robot was doing, its reliability status and the presence of a face on the robot, help the user trust the robot better. It was noted that style and modality of communication with the inclusion of some etiquettes, robotic emotional expressions and gestures in the feedback could influence performance of users using the automated system [20].

Timing of the feedback is also critical to maintain comprehension of the information being communicated [36]. For instance, feedback given too late causes confusion [19]. Temporal immediacy between a user's input and the robot's response influences the naturalness of the interaction [37]. To increase the trust of the user it is important to provide continuous feedback regarding the reliability of the robot [38]. This agrees with the findings in [32, 36] related to providing a continuous stream of information. The question of which information to provide continuously and which information to reserve for the user's demand arises. This often varies based on the type of task, feedback modality, and the type of potential users [39]. The preference of the user regarding feedback timing along with the content and mode of feedback in specific tasks is essential to foster smoother coordination and collaboration between the human and the robot.

In previous studies involving person-following robot applications, most of the developments did not explicitly incorporate feedback from the robot regarding the robot's actions as it follows. The robot simply followed the target person as soon as the person was detected in a predetermined range as noted in [2]. This caused confusion for many of the participants regarding what the robot was doing per time. Several participants were unsure if the robot was following them, stopping or had lost track. This lack of communication from the robot could lead to a loss of SA which makes the users uncertain or unsure of the state of the interaction at each point in time [40]. This could potentially degrade the interaction quality of the older people with the robot. The few studies that incorporated feedback [41–43] provided message acknowledging user commands such as saying 'yes' or other specific expressions [42]. These were implemented as part of the robot's behavior without explicit user studies to determine the preferred content, mode or timing of feedback from the robot. There is generally a gap in user-centered preferences in design of feedback for person-following robots [2], particularly those used in eldercare [11].

The current study presents a user-centered design approach to ensure the design is focused on older adults' needs and preferences. Older adults' preferences for feedback design were evaluated in a series of empirical studies. Feedback design was constructed consecutively, looking first at the preferred robot LOT (perception, comprehension, projection), and the content of the information to be presented (depending on the LOT), followed by the mode (voice or tone) timing and frequency of the feedback (continuous or discrete). It is crucial to note that while identifying preferred feedback parameters, individual differences come into play [44]. There are several sources of individual differences in older adults which usually have potential implications in the design process [10, 44]. Two of the sources, which were considered in this study were age and gender. The influence of these factors in the feedback design was highlighted through the analyses. The aim was to improve quality of interaction taking into account the different age groups and gender, while ensuring increased user satisfaction and acceptance.

This paper presents comprehensive analysis of our previous study [5] which highlighted the importance of the feedback design considerations but did not provide the details and lacked in-depth analyses. Additionally, we provide new analyses regarding the influence of gender and age on the feedback design. Analyses on influence of predisposition of the participants to robots before interaction is also included. Finally, the paper presents design guidelines for feedback design in the development of an assistive person-following robot for older adults.

3 Methods

3.1 Overview

The study was constructed with a coactive design perspective. It involved preliminary discussions with older people on their expectations about a robot in the context of person-following. This aligned the thoughts of the potential users and designers into the same conceptual design zone ensuring robot performance is tuned to meet the users' expectations. The highlights of these preliminary discussions bordered on the overarching goals of the robot such as what the robot does, why and how. This laid the foundation of the intentional model of transparency on which the specific task related model of transparency addressed in the current study was built. Preliminary experiments were also conducted to explore proxemics and movement preferences of the robot as it follows the user in different environmental conditions [5]. These provided some environment related preferences, constraints and context which guided the feedback design options in the current work. In this research, a sequence of experimental user studies with older adults were performed to evaluate step by step:

1. *What* level of transparency *would the older adults desire and what would they prefer as feedback content at their desired LOT?*
2. *Which* feedback mode *would the older adults prefer?*
3. *What would the preferred* feedback timing *be?*

The design parameters gathered in these user studies were implemented and tested in a final experiment to evaluate the effectiveness of the feedback design. This experiment evaluated if the feedback implementation improves the quality of interaction.

3.2 Apparatus

A Pioneer LX mobile robot (50 cm width, 70 cm length and 45 cm height) equipped with an integrated on-board computer, 1.8 GHz Dual Core processor, and 2 GB DDR3 RAM was used.

A built-in SICK S300 scanning laser rangefinder (LRF), mounted approximately 20 cm above the ground, was used to detect nearby obstacles and stop the robot if it detected an object 50 cm from its core. The robot also possesses a Kinect camera with a pan mechanism that was added to the robot and mounted 1.5 m from the ground, as shown in Figure 1. The person tracking and following commands were developed and executed in ROS [45] and were sent to the Pioneer LX's onboard computer using a TPLINK router with wireless speed up to 300 Mbps.

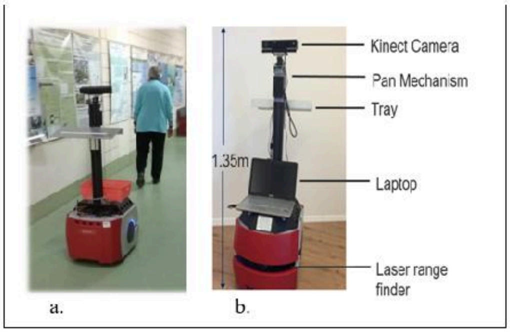

Figure 1: (a) A participant being followed by the robot; (b) Experimental platform – Pioneer LX mobile robot.

3.3 Algorithm development

The algorithm works without a map. This is important to ensure flexible operation in a multitude of environments. The map of the environment used in this study is presented in Figure 2. Open Track [46, 47] is used to identify and track the coordinates of the person to be followed. Some adjustments were incorporated to ensure it can detect a human 1.4 m to 2 m tall, with a confidence level threshold of 1.1.

The robot selects the first person detected and moves the robot to the defined position behind the person. The person-following algorithm to move the robot in this manner is described in a previous study [48]. Continuous estimation of the person's position is achieved using the robot's pan angle ($\mathbf{R_{angle}}$) and the angle of the detected person ($\mathbf{P_{angle}}$), measured from the centre of the robot, to constantly estimate the position of the person. The angular error ($\mathbf{E_{angle}}$) was measured as the difference between the angle of the person from the centre of the robot. The person's position (coordinates X,Y) is calculated as follows:

$$X = distance(cos(P_{angle} + R_{angle})) \tag{1}$$

$$Y = distance(sin(P_{angle} + R_{angle})) \quad (2)$$

The linear velocity ($\mathbf{l_{vel}}$) of the robot is updated dynamically based on the distance between the robot and the target using the distance proportional controller ($\mathbf{K_{pdist}}$). The angular velocity ($\mathbf{a_{vel}}$) is also updated dynamically based on the angular displacement of the target with the aid of angle proportional controller ($\mathbf{K_{pangle}}$). These are calculated as follows:

$$l_{vel}[t_1] = l_{vel}[t_0] + (K_{pdist} * (distance - target)) \quad (3)$$

$$a_{vel}[t_1] = a_{vel}[t_0] + (K_{pangle} * E_{angle}) \quad (4)$$

Parameters were set according to recommendations for socially-aware person-following robots [2, 3, 22, 27, 49]. The maximum following speed was set to 1.0 m/s for safety reasons as emphasized in [5, 50, 51]. Other parameters such as acceleration coefficient (implemented using the proportional controller), following distance and following angle were set to 0.5, 0.3 m and 30°, respectively.

The robot's collision avoidance mechanism was set to stop within the specified following distance (0.5 m). To achieve this, the LRF of the robot estimates the position of the robot to the person or any other obstacle, and proportionally reduces the speed of robot within distances of 0.5 m and 1 m. This continues until the robot finally stops at a distance of 0.5 m from the obstacle or person to avoid collision. This is similar to the technique used and described in previous studies conducted [48].

A summary of the algorithm for the person detection and following [4, 52] is presented in Table 2 below.

Table 2: Person detection and following algorithm pseudo-code.

Algorithm for the Person detection and following

Initialize:
  $linear\_velocity\ (l_{vel})$, $angular\_velocity\ (a_{vel})$,
  following distance (d), **following angle** (a),
  acceleration_coefficient (K_{pdist}),
  angular controller (K_{pangle});
for each person detected [**i**], at time [t], **do**
  estimate position of person: x_{person}, y_{person}
  compute angle error of robot:
    $y_{error} = y_{person} - sin(a)\,d$
    $x_{error} = x_{person} + 0.4 - cos(a)d$
    $angle_{error} = tan^{-1}(\frac{y_{error}}{x_{error}})$
  compute distance error of robot:
    $dist_{error} = \sqrt{x_{error}^2 + y_{error}^2}$
  update vel. of robot with prop controller:
    $l_{vel}[t_1] \leftarrow l_{vel}[t_0] + (dist_{error} * K_{pdist})$
    $a_{vel}[t_1] \leftarrow a_{vel}[t_0] + (angle_{error} * K_{pangle})$
  safety measures; collision avoidance
  send vel. update to robot motion planner
end for loop

3.4 User studies

A sequence of user studies was conducted as presented in Figure 3. Each experiment was independent with the outcome of preferences from each experiment implemented in the succeeding experiment.

3.5 Procedure

Before each experimental session, participants completed a preliminary questionnaire. This included demographic information, the Technology Adoption Propensity (TAP) index [53] and the Negative Attitude toward Robots Scale (NARS) [54]. They were then introduced to the robot and to the experimental task. The task was to walk down a straight 25 m path to retrieve an object and place on the robot. The robot was expected to follow the participant and communicate with the participant by voice in English as it follows. The audio feedback was provided directly by the robot's speakers which produced a sound of approximately 60 dB above the noise level in the building which was about 40 dB. The robot followed at a specified distance, angle and speed (section 3.3). The study took place in a 2.5 m wide corridor of a university laboratory building as seen in the snapshot of Figure 1a and in the map of Figure 2.

A trial refers to each session when the participants interacted with the robot which includes walking the designated path with the robot to retrieve a specified item at a specified location. A video of each trial was taken and saved for analyses where objective measures were carefully assessed. In each experiment there were two experimenters, who documented observations. One of the experimenters took care of explaining instructions to the users while the other experimenter ensured safety of the participants as the robot follows (one of the tasks was to be responsible to stop operation using the emergency button in case of a problem).

After each trial, a condensed form of Situation Awareness Rating Tool (SART) [55] was used to assess the level of situational awareness and understanding the participants had in each session. This was administered along with some other questions relating to the preference of the participants in each session as used in [30]. The post-trial questionnaire used a 3-point Likert scale with 3 representing "Agree" and 1 representing "Disagree". The 3-point scale was selected based on previous trials with older adults that revealed that they experienced difficulty

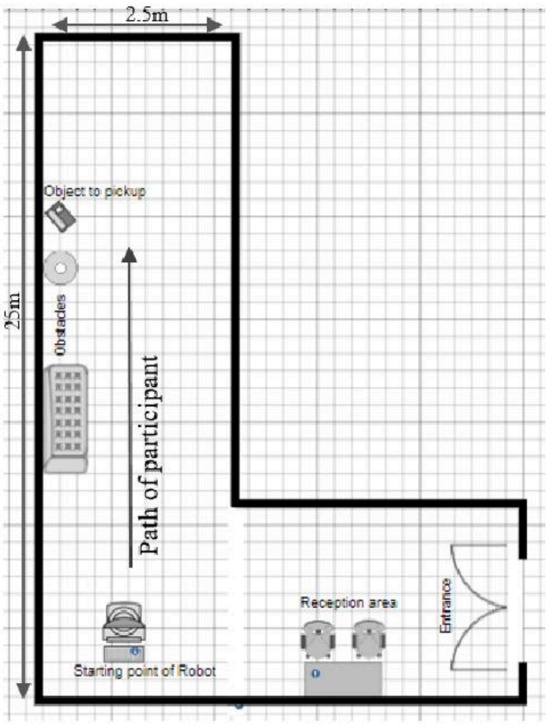

Figure 2: Map of the environment in which experiments were performed.

and sometimes confusion in the process of indicating their opinion/preferences on the 5- or 7-point scales [5]. At the end of all trials, a final questionnaire was provided to enable the participants to express their opinion regarding the experience with the robot. All procedures were approved by the university's ethical committee.

3.6 Analyses

The analyses were performed using the following objective and subjective measures acquired during the experiments as detailed below:

Objective measures: were assessed by analysis of the videos acquired during the experiment.

Understanding was measured as the number of clarifications made by participants to the experimenters while interacting with the robot. These sometimes created interruptions during the experiment. An interruption in this context is the period during the experiment when the participant does not understand the information the robot is presenting or what the robot is doing and therefore pauses to ask the experimenter questions for clarification regarding the information the robot was giving. Another measure of understanding was the reaction time which was measured as the time it took participants to respond to the robot's instructions. Effort was measured based on participant's heartrate before and after each trial. The heartrate was measured with a Garmin watch Forerunner 235 series. The watch was worn by the participants at the start of the experiment till the end of the experiment. The heart rate readings (bpm) was taken at the start and end of each trial and used in the analyses [56, 57]. Engagement was measured based on the duration of gazes the participants made to the robot during communication, total time spent with the robot, and number of times participants initiated communication with the robot while gazing at the robot). Trust was measured via the overall time spent on the task of walking to pick item without looking back at the robot coming behind and the time spent waiting for the robot when the robot lost track or delayed. Comfortability was measured as the number of times participants were glancing back at the robot.

Subjective measures: Users' responses regarding their level of understanding, comfort, engagement, persuasiveness and satisfaction were assessed through questionnaires and short interviews at the end of each experimental trial.

Data Analyses: The tests were designed as two-tailed with a significance level of 0.05. The model for the analyses was the General Linear Mixed Model (GLMM) with user ID included as a random effect to account for individual differences among participants.

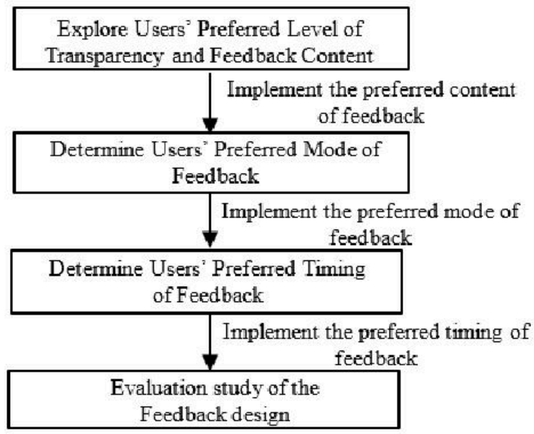

Figure 3: Experimental flow of the user studies.

4 Level of transparency and content of feedback

The aim of this experiment was to provide the users sufficient situation awareness without overwhelming them with excess information. The preferable level of transparency was explored along with the appropriate information content.

4.1 Experimental design

Independent Variables: Level of transparency was the independent variable. Three levels of information were presented to the participant by the robot. At the perception level of transparency, the robot communicated to the participant **what** it was doing (e.g., 'following', 'stopping'). At the comprehension level of transparency, the robot communicated to the participant **why** it was doing what it was doing (e.g., 'stopping because the participant stopped, 'stopping because of an obstacle'). At the projection level of transparency, the robot communicated to the participant what it was **planning to do next** (e.g., 'I will stop whenever you stop').

Dependent Variables: Preference regarding the amount of information participants wanted the robot to present to them was collected through questionnaires and short interviews that contained specific items related to the participants' understanding of the robot's feedback, level of comfort and mental workload while interacting at various levels of transparency. The mental workload assessment was included due to the mental effort that could be required by the older adults to process the information the robot is presenting to them [11, 44]. The robot presented some information to the participants as described earlier. The participants were then asked for their preferences through questionnaires. They were also given the opportunity to add other expressions or information they would want the robot to give in addition to what it was already presenting to them. These responses from the participants were collected through questionnaires and interviews.

Participants: Thirteen older adult participants (8 Females, 5 Males) aged 65-85 were recruited. They were all healthy participants with no physical disability, vision or hearing impairment. A short interview was held with them before the experiment commenced to ascertain their comfort with the experiments and understanding of the procedure. Each participant experienced all three levels of information presentation from the robot in random order. They completed the study separately at different time slots, so there was no contact between participants.

4.2 Results

Analysis on LOT preferences (Figure 4) revealed significant differences among users (M=1.62, SD=0.87, p<0.001). All of the participants preferred the robot to say what it was doing at the moment (LOT level 1). 38% (M =0.38, SD=0.5) of the participants wanted the robot to additionally present the reason for its actions (LOT level 2), while only 23% (M =0.23, SD=0.44) of the participants wanted information on future actions of the robot (LOT level 3).

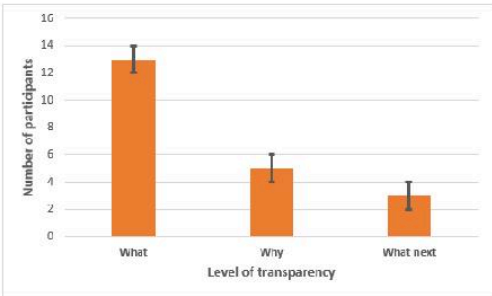

Figure 4: User preference regarding level of transparency.

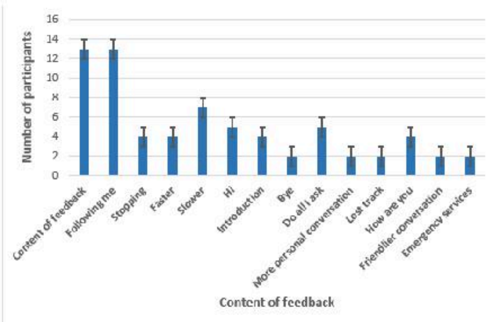

Figure 5: Users' suggestions for content of feedback.

Participants did not express discomfort or excess workload while interacting with the robot at higher LOTs. They also gave their preferences for specific feedback content from the robot (Figure 5). Several participants wanted it to say more than basic task related information such as 'following' or 'stopping'. Some wished it would introduce itself and greet them. Most of the participants (85%) also desired that the robot communicates in their native language (Hebrew).

The results provided the rationale for the use of the first LOT (robot's current action) with specific expressions such as 'starting', 'following', 'stopping' in the next experimental stage. Greetings according to the suggested content (such as 'hello' or 'bye') during the interaction with the robot were added to the communication to make it friendlier. This modification was implemented for subsequent studies by enabling the users to choose the preferred language of feedback (English or Hebrew).

5 Mode of feedback

The aim of this experiment was to identify the most suitable mode of feedback considering the fact that the robot is a person-following robot which is expected to be positioned behind the user most of the time. This requires the feedback to be audible to the user particularly when following. Two audial feedback modes were explored: a female voice (as recommended in [10] and [11]) and a tone in form of a sequence of beeps ('beep', 'beep'...). The voice content was: 'following', 'stopping', and greetings. The voice was in the form of a recorded human speech in order to obtain a sound as close as possible to natural human communication. The beeping started once the robot began to follow and ceased when it stopped. The sound of the voice and tone feedback was maintained at approximately 60 dB, well above background noise level. The volume was made adjustable to the preference of the participant, such that it could be increased or decreased to make it comfortable and audible to the participant in accordance with audial feedback design guidelines provided [44].

The feedback modes were implemented according to design guidelines for general multimodal human-robot interaction [58]. The standards for developers to address the needs of older persons [10, 11] was also consulted in order to satisfy design recommendations for presentation of auditory information. Actual human speech was used instead of synthesized speech based on earlier studies which revealed that it aided higher intelligibility [59]. A native speaker's recording was used in order to avoid accent-related difficulties in understanding the communication of the robot [60]. The content of the feedback was based on the results obtained in the previous stage.

5.1 Experimental design

Independent Variables: The mode of feedback manipulated as voice mode or tone mode.

Dependent Variables: subjective and objective measures as described in section 3.6.

Participants: Twelve additional older adults' participants (9 Females, 3 Males) aged 62-73, were recruited. They were physically and cognitively fit for the experiments as described in section 4.1. Each participant received feedback from the robot in both tone and voice modes.

5.2 Results

Analysis revealed that 10 of the participants (77%) preferred the voice feedback mode ($M=0.77$, $SD=0.43$) to the tone mode ($M=0.08$, $SD=0.272$) and 8% were fine with either of the modes ($M=0.15$, $SD=0.368$). This effect of feedback mode on their preference was significant ($M=0.92$, $SD=0.484$, $p<0.001$). Feedback mode had no significant effect on comfort, engagement and persuasiveness. Eight of the 12 participants reported that they were comfortable in both trials. Three of the participants were indifferent. This outcome is presented in Figure 6.

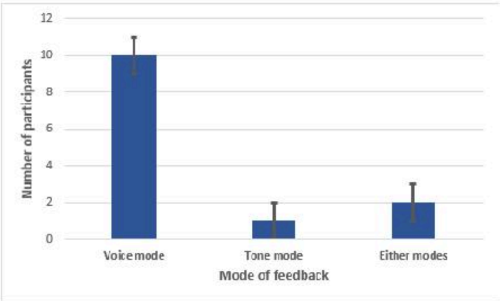

Figure 6: Users' preferred mode of feedback.

The heart rate variability was also not significantly affected by the feedback mode. A one-way ANOVA using mode of feedback as the fixed factor and user ID as a random effect revealed that the mode of feedback had a statistically significant effect on the users' **understanding** ($M=2.0$, $SD=0.938$, $p<0.001$). Voice feedback was therefore used for the subsequent experimental stages.

6 Timing of feedback

The temporal dimension of the feedback preference of the older adults was studied. The transparency level, content and mode of feedback were based on the outcome of the previous stages.

6.1 Experimental design

Independent Variables: the timing of feedback included three timing options: continuous (5 and 10 seconds intervals) and discrete. As an example, in the continuous timing mode (5 seconds interval), the verbal feedback was given continuously, every 5 seconds (e.g., 'following', 'following', every 5 seconds). In the discrete timing mode, the feedback was given only at the beginning and at the end of the interaction with the robot. In this mode, the robot would simply inform the participants when it begins the following and inform the participants when it is stopping.

Dependent Variables: the same variables described in section 3.6

Participants: The same 12 participants recruited in 5.1 followed up in this experiment. Each participant received verbal feedback from the robot in the discrete and continuous timing options. They answered brief questions in questionnaire and interview format after the trials regarding which feedback timing they prefer and why.

6.2 Results

Analyses showed that 80% (10) of the participants preferred the continuous feedback (*M=0.85, SD=0.366*) over the discrete feedback with (*M=0.15, SD=0.366*). The effect of the feedback timing on the users' preference was statistically significant (*M=1.46, SD=0.756, p<0.001*). The effect of feedback timing as a fixed variable on understanding was also statistically significant (*M=1.87, SD=0.923, p<0.001*). Among those who selected the continuous feedback as their preferred timing mode, 84.6% preferred an interval of 5 seconds (*M=0.69, SD=0.468*) over 10 seconds (*M=0.15, SD=0.366*). The reason given was better awareness of what the robot was doing behind them at every point in time. This provided a rationale for the use of continuous feedback at the rate of 5 seconds in the succeeding quality of interaction evaluation experiment.

Table 3: Objective measures.

Variable	Objective measures
Engagement	Gaze duration (seconds)
Understanding	Number of interruptions to ask for more clarification (counted)
	Reaction time (seconds)
Trust	Overall time spent on the task of walking to pick item without looking back at the robot coming behind (seconds)
	Time spent waiting for the robot when the robot lost track or delayed (seconds)
Comfortability	Number of times participants were glancing back at the robot (counted)

7 Does the feedback implementation improve the quality of interaction?

The feedback design parameters obtained in the three previous user studies were evaluated to examine their effects on the quality of interaction relative to a person-following robot with no feedback.

Hypotheses: the feedback design implementation will improve the quality of interaction with the specific hypotheses stated as follows assuming that the feedback:

H1: will improve the engagement of the participants.
H2: will increase the understanding of the robot for the participants.
H3: will improve the trust the user has in the robot.
H4: will improve the comfortability of the participant.

7.1 Experimental design

Independent Variables: There were two groups: one group interacted with the robot without feedback, the other group interacted with the implemented feedback.

Dependent Variables: Quality of interaction was measured both objectively and subjectively in terms of engagement, understanding, trust and comfort [6].

Objective Measures: Engagement, understanding, trust and comfortability were measured as explained in section 3.6. A summary of the objective measures used are presented in Table 3.

Table 4: Feedback design parameters.

Parameter	Preference	Description
Level of transparency	Level 1 LOT	Information on what the robot is currently doing.
Content of feedback	Action of the robot, Friendly content	Specific information such as 'starting', 'following', 'stopping' Greetings from the robot.
Mode of feedback	Voice feedback	Audible female voice with speech rate less than 140 wpm with adequate pauses at grammatical boundaries.
Timing of feedback	Continuous feedback (5 seconds interval)	Notification of the state of the robot every 5 seconds (like, 'following', 'following' ...)

Subjective Measures: Questionnaires and short interviews regarding their comfort level, understanding of the robot's information, trust and satisfaction as explained in section 3.6.

Participants: 20 older adult participants (13 Females, 7 Males) aged 65-85. They were healthy participants with no major physical disability. Ten of the participants received feedback from the robot while the other 10 received no feedback from the robot. Additional analyses were conducted to explore the potential influence age and gender of the participants could have on the QoI variables assessed. Analyses to evaluate the influence of the predisposition of participants on the QoI was also conducted. The influence of age of the participants was assessed by conducting a correlation analysis between the age of the participants (*M=78.84, SD=6.72*) and the different QoI variables. Similar analyses were conducted for the correlation between gender and QoI as well as between the responses of participants to the NARs questionnaire and QoI.

Feedback Design: Feedback was designed using the preferred parameters identified in the preceding stages as detailed in Table 4.

7.2 Results

7.2.1 Attitude towards technology

Most of the participants were acquainted with the use of innovative technologies (*M=3.39, SD=0.72*). The TAP index [21] revealed that more than half of the participants were affirmative that technology could provide more control and flexibility in life (*M=2.48, SD=1.59*). Several of them also showed confidence in learning new technologies (*M=2.95, SD=1.18*), and trusted technology (*M=3.04, SD=1.58*). The NARS index [55] revealed that about 60% of the participants felt that if they depended too much on the robot, something bad might happen (*M=3.05, SD=1.19*).

7.2.2 Engagement

The results revealed an increase in the time (*M=3.15, SD=4.38*) the participant was focused on the robot while the robot was presenting some information about the interaction before following (*F(1,37)=20, p<0.001*). In the group where the feedback was implemented, it was observed that participants were willing to spend more time communicating with the robot (*M=5.65, SD=4.65*) compared to the group without feedback (*M=0.53, SD=1.88*). There was a 60% improvement in the communication frequency suggesting improved engagement.

Responses from the questionnaire also showed significant differences in the response of the participants related to engagement (*M=2.38, SD=0.74, p<0.001*). Participants in the group with feedback (*M=2.76, SD=0.54*) made more positive comments regarding the naturalness of the robot that made them feel more connected to the robot compared to those in the group without feedback (*M=1.96, SD=0.72*). Several of the participants in the group with feedback expressed excitement at the robot's communicative ability. Some of the comments made were: 'I was thrilled to hear the robot communicate with me in Hebrew. It helped me relate better with it', 'the way it spoke every time, telling me what it's doing made it interesting to interact with'. These comments suggest some form of engagement with the robot.

7.2.3 Understanding

The understanding of the participants improved with the feedback design as expressed by the amount of time (*M=2.84, SD=3.81*) the participants impeded the flow of the interaction due to clarifications they were making regarding the actions of the robot (*F(1,37)=3.7, p<0.062*). Participants in the group with feedback experienced a smoother flow in the interaction with minimal interruptions (*M=0.75, SD=1.12*). Participants in the group without feedback interrupted the flow of the interaction more frequently when they were not certain of what the robot was doing (*M=5.05, SD=4.39*).

In terms of the reaction time (*M=2.2, SD=1.84, p=0.013*), participants in the group with feedback (*M=2.9, SD=1.94*) spent more time (seconds) listening to the instructions from the robot before taking action (*F(1,37)=6.76, p<0.013*) compared to the group without the feedback design (*M=1.47, SD=1.42*). Additionally, the participants' responses in the questionnaires regarding understanding (*M=2.32, SD=0.66, p<0.001*) showed that the group with feedback (*M=2.76, SD=0.54*) had a better understanding of the robot than the group without the feedback (*M=1.83, SD=0.37*).

7.2.4 Trust

Results revealed that the participants focused on the task without worrying about the robot coming from behind when the feedback was implemented (*M=76.95, SD=20.08*), as seen in the time they spent in the task of picking up an item (*M=99.33, SD=32.95*). This was statistically significant, (*F(1,37)=36.78, p<0.001*) compared to the time spent in the group without feedback (*M=122.89, SD=26.9*). This suggests they gained some level of trust that the robot would not collide with them or cause any harm to them. Participants in the group with feedback (*M=0.75, SD=1.12*) waited (*M=2.85, SD=3.81*) less compared to participants in the group without feedback (*M=5.05, SD=4.4*). This could have been due to better awareness of what the state of the robot was if it was delayed or lost track. This was also statistically significant (*F(1,37)=18, p<0.001*).

7.2.5 Comfortability

Regarding comfortability as measured by the number of back glances (*M=2.9, SD=3.6*) the participants made, there was no significant difference (*F(1,37) =0.073, p=0.88*) between the participants in the group with feedback (*M=3, SD=4.05*) and those in the group without feedback (*M=2.68, SD=3.15*). A significant difference was however found in the comfortability of communicating with the robot (*M=2.37, SD=0.7, p=0.004*) based on the questionnaire responses. Participants in the group with feedback (*M=2.67, SD=0.66*) responded more positively regarding comfortability with the robot than those in the group without feedback (*M=2.05, SD=0.66*).

The influence of the feedback on the QoI variables as measured in the objective variables is presented in Table 5.

Table 5: Influence of feedback implemented on QoI variables.

		Engage	Understand	Trust	Comfort
NFD	Mean	0.53	1.47	122.89	2.68
	SD	1.88	1.42	26.9	3.15
WFD	Mean	5.65	2.9	76.95	3.00
	SD	4.65	1.94	20.08	4.05
	Sig.	<0.01**	0.01*	<0.01**	0.88

**p<0.05, **p<0.01, NFD = No feedback, WFD = With feedback, Engage = Engagement, Understand = Understanding, Comfort = Comfortability*

7.2.6 Influence of initial attitude of participants

Correlation analyses were conducted to explore the possible relationships between the predisposition of the participants in form of NARS index and the objective variables. These were conducted using Pearson's Correlation Coefficient analyses to determine the trend, significance and effect size. A significant positive correlation was observed between the NARS index of the participants and engagement (*r=0.51, n=20, p=0.021*). Participants who had more negative reaction towards the robot gazed more intently at the robot.

There was also significant positive correlation between the NARS index of participants and the level of understanding in terms of number of interruptions made to ask for clarification (*r=0.491, n=20, p=0.028*) and reaction time (*r=0.448, n=20, p=0.047*). Participants who were more negatively disposed to the robot seemed to ask more questions about the robot and also had a longer reaction time to the robot's requests.

There was a negative correlation between the NARS index of participants and the trust the participants had in the robots. The more negative predisposition the participants had regarding the robot, the less they trusted the robot as observed in the duration of time they spent on the task with the robot (*r=-0.558, n=20, p=0.01*) and the duration when they waited for the robot (*r=-0.362, n=20, p=0.116*).

The relationship between the NARS index of participants and their comfortability was positive but was not significant (*r=0.071, n=20, p=0.763*).

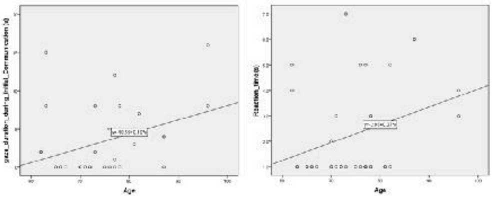

Figure 7: left) Correlation between age and gaze duration; right) Correlation between age and reaction time.

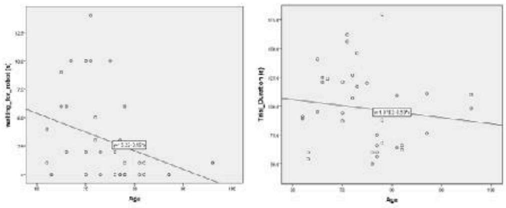

Figure 8: left) Correlation between age and waiting time; right) Correlation between age and time spent with the robot.

7.2.7 Influence of age group and gender

There was a statistically significant positive correlation between the age and the engagement as measured by gaze duration (*M=3.84, SD=4.34, r=0.56, n=20, p=0.004*). This is depicted in Figure 7. As age increases, the participants tend to gaze more at the robot during communication.

There was also a trend between the age and the understanding of the participants as assessed in terms of the number of clarifications made by the participants (*M=0.4, SD=0.5*) and the reaction time in seconds (*M=2.27, SD=1.86*). The correlation between the age of the participants and the number of clarifications made by the participants was not significant (*r=0.097, n=20, p=0.568*) but there was a fairly significant positive correlation between age and reaction time, (*r=0.32, n=20, p=0.056*). As the age increased, slower response to the robot's instructions were observed. This is presented in Figure 7.

The trend between age and trust, which was measured in terms of the duration when the participants waited for the robot when the robot lost track (*M=2.4, SD=3.79*), was also explored (Figure 8). It was observed that that there is a significant negative correlation between age and the waiting duration (*r=-0.443, n=20, p=0.027*). There was no significant correlation between the age of the participants and their level of comfortability as assessed by the number of back glances made to the robot while walking (*M=2.9, SD=3.6, r=-0.287, n=20, p=0.164*) and the total time they spent with the robot (*M=2.9, SD=3.6, r=-0.231, n=20, p=0.267*) but the analysis reveals some negative trend with age (Figure 8).

With regards to gender analyses, the females (*M=7.6, SE=1.36*) seemed more engaged (*F(1,13)=4.5, p=0.054*) as seen in the gaze duration (*M=5.51, SE=0.86*) compared to the males (*M=4, SE=1.01*). The males (*M=2.05, SE=0.72*) also seemed to trust the robot less than the females (*M=3.94, SE=1.85*) as observed in the duration of time spent (*M=2.84, SE=0.837*) with the robot, (*F(1,12)=0.898, p=0.362*). In terms of understanding, as assessed through the number of clarifications made (*M=0.61, SE=0.13*), it was observed that the females asked more questions than the males, but this was not statistically significant, (*F(1,23)=0.123, p=0.729*). The differences in the level of comfortability each gender experienced as assessed by the number of times they glanced back at the robot (*M=2.23, SE=0.675*) and the amount of time they spent with the robot (*M=93.24, SE=9.11, p=0.934*) was also not statistically significant (*F(1, 23)=0.007, p=0.934*).

8 Design guidelines

This is a first attempt to explore feedback parameters via a series of user studies focusing on a person-following robot application for older adults. This sequential user-centered study aimed to ascertain the older adults' user needs and preferences regarding feedback from the robot for this defined task of person-following. The implications of this series of sequential studies as relating to improved feedback design are presented in the following subsections.

8.1 Transparency considerations

Users prefer information on what the robot is doing (LOT 1). Hence, they do not need the robotic system to be fully transparent, rather they want it to be current and immediate. They are satisfied with the ***robot communicating just its current actions and status information.*** Older adults seem to trust that the robot will know how to handle itself if more information is available or if the state of matters will change despite their initial disposition to the robot as revealed in the NARS index. This agrees with the discussions in [27] where it was hypothesized that the users may prefer less information based on the degree of trust they have developed in the system. Users' preference in our first study also concurs with the design principles for transparency, outlined in [20] where designers were cautioned regarding providing too much information to users.

It was emphasized that if such information exceeds the preferences and needs of the users, it may bring frustration and/or confusion. It also agrees with findings in [36] which noted that providing too much information results in information overload and decrease of users' performance.

In order not to limit the participants to receive feedback only for task-related transparency options, participants were asked to suggest additional information that they would want the robot to give. This was to make room for other aspects of transparency relating to the robot such as information on how the robot makes its decisions or principles guiding its actions. The discussion was also intended to address environment-related feedback content such as structure of the environment, constraints in the environment and safety-related information about the environment. Caution was taken to avoid overloading the participants with too many transparency options. Therefore, transparency models connected with teamwork (information on the role of the robot and human in task), human state (information regarding physical, emotional or stress state of the participant) were not mentioned. Participants were asked to point out specific content they would like the robot to give. Participants' responses (Figure 5) indicated that they were interested in task-related transparency information (such as 'following', 'stopping'). In addition, some participants wanted the robot to ask about their wellbeing (greetings, e.g., 'how are you?'). These are aspects of the human-related model of transparency which participants provided without being directly asked. It supports the significance of 'thinking aloud' sessions recommended in user-centered system designs [28]. The preference for greetings also supports the finding of Sabelli et al. [61].

The outcome of the first stage also brings to the fore an interesting contrast in the LOT demands of younger and older adults. In a previous study [32], earlier discussed, where younger adults (aged 18-22) participated in a user study to examine the effect of transparency and feedback modality on trust, they preferred higher LOTs. This may not only be an age-related trust issue but may also be connected with the embodiment of the robot. The robot in [32] was simulated on a computer desktop and not physically present as used in the current study. This suggests that interacting with a physical robot and observing its performance may have a stronger effect on the users' trust and affect the amount of information (LOT) such user may prefer the robot to provide compared to a simulated robot.

The population in this study may be unique in their LOT demands, but we cannot assure this conclusion since the studies were composed of a specific task. To establish a stronger mapping between the preferences in this study and that of a wider population of older adults, more extensive studies are recommended as suggested in [62]. These further studies would assess the external validity of this outcome on a larger scale. Studies that examine the possible changes in users' transparency demands such as trust and comfortability adaptation for interacting with a robot occurs over longer periods of interaction.

8.2 Feedback modality considerations

Users prefer the robot to communicate with them in voice mode. The voice, as compared to tone-mode, tends to give the robot a form of personality which enables users to better envision it as an assistant or partner than just a mere machine. This tallied with the findings in [63] where it was highlighted that verbal mode improves perceptions of friendship and social presence. Even though, the outcome in [32] seemed to portray that feedback modality was not significant, the task was different which emphasizes the importance of evaluating the feedback design parameters in specific tasks to ensure applicability to such tasks as recommended in the study [32] and in [27]. This also agrees with the recommendations in [20], regarding designing communicative interfaces to ensure that the feedback modality fits the needs and preference of the user in defined tasks. In the current task, where the robot follows the user, the feedback modality (voice feedback) tends to keep the users more engaged with the robot which is one of the variables that indicates a potential of improvement in the quality of interaction.

Identifying a primary means of feedback was crucial in this study particularly in connection with the preferred content of the feedback. Providing multiple modalities can be explored as a next stage, with the possibility of including haptic feedback. However, considerations must be made regarding the cognitive peculiarities of the older adult users which influence the number of sources of information they can process per time [10], [58]. It is pertinent that the older adults are not overloaded with information. There is the potential of adaptable modality selection [36, 39, 64] which may provide the option of user-defined modality preferences based on the complexity of task, human physical or cognitive state, performance and environmental related factors. This would give the older adult allowance to further personalize their feedback modality preferences which aligns with the goal of meeting the needs, preferences, capabilities and limitations of users [39, 44, 65].

8.3 Feedback timing considerations

Continuous feedback, at short intervals, was preferred by the participants. It seemed to provide them with better awareness regarding the state of the interaction compared to discrete feedback used in previous studies. This was in conformity with previous studies where continuous feedback timing was found to improve users' awareness [36, 38, 66] even though these studies were not focused on older adult users. The outcome of this stage therefore highlights a crucial feedback design component of ***providing minimal information* (LOT1) *continuously at short intervals***. We would however recommend that this preference be treated with caution, as preference of the users could change with the complexity of the task or the duration of interaction. On a long term basis, participants may adapt their level of trust in the robot and this may make them rely on the robot more, such that longer intervals between continuous feedback messages may be preferred. Different degrees of involvement of the robot in the task may also influence the frequency of information required by the participants [20, 26]. Users may require information less frequently from a robot that is more autonomous than one which is more dependent on the user for each action. This concept of the influence of the robot's level of autonomy on feedback timing in the context of person-following task for older adults requires further exploration.

8.4 Predisposition considerations

The results observed from the correlation analyses of the effect of the initial attitude of participants as indicated by the NARS responses revealed the impact that the predisposition of the participants towards robots could have on their interaction with the robot. This reflects previous findings [55] where it was explained that the initial attitude of the participants affected the manner they evaluated the robot which then influences the interaction [55]. Bishop et al. [67] had highlighted the negative influence that subjective negative affect could potentially have in the interaction with a robot. This could be responsible for the trends seen where participants who had a more negative initial attitude towards the robot even before interaction (with or without the feedback) seemed to understand less and also trust it less.

It is therefore important to include some form of introductory session by the robot to better prepare the older adult for the interaction. The feedback design parameters and interfaces should make allowance for such user-friendly initial introductions before the actual task implementation with the robot. The older adults should however, also be given the option to skip this session if they are already familiar with the robot so that this introduction session does not induce boredom in the interaction. Such a session can also help overcome the novelty effect [68] and provide basic training so as to ensure focus is on the specific study parameters.

8.5 Gender and age considerations

Results revealed that age and gender could influence the perception, preferences and attitudes of the participants towards the robot. Even though, there may be some intra-individual differences that may also be responsible for some of the observations made [44], results in this study revealed that the inter-individual differences stemming from age and gender are worth considering in the design. Thus, in the process of developing a user-centered feedback design, the preferences of women should be considered differently from that of the men. The feedback parameters should be tuned to suit the preferences of older adult users in different age categories.

For example, regarding engagement, the trend reveals that the older old adults tend to be more engaged with the robot compared to their younger counterparts as seen in the gaze duration analyses. This could be connected with novelty effect where a larger percentage of the younger old adults may have been more familiar with some form of related technologies compared to the older old adults [7]. This could inspire more attraction to the robot, and thus engage them more. This agrees with previous findings [67] where it was shown that familiarity with related technology negatively correlates with the attitude and intention to interact with the robot. Those who were more familiar with related technology may find the interaction less enjoyable and thus may not be as engaged as those who are less familiar [67]. Attention has to be placed on measures to improve the engagement in the younger older adult category.

It was also understandable that the older-old adults had a longer reaction time when interacting with the robot as seen in the correlation of age with understanding. Several older old adults do not have as much experience with technology as the younger old adults as observed in Heerink's study [69]. It was additionally established in the study that experience with related technology aids the use of a system [69]. This could explain the reason why the younger old adults who likely had more experience with technology seemed to have a better understanding of the robot's operation compared to the older adults. It also emphasizes the importance of adapting some of the feedback parameters such as clarity, repetition of instruction, rate of feedback to aid the understanding of the older old adults.

The older old adults seemed to trust the robot more than the younger old adults as seen in their waiting time. This also agrees with the discussions in [67] where it was stated that younger users who may be more familiar with related technology were more aware of the robot's limitations and therefore may have felt less safe around the robot. This could affect the trust the more familiar people felt around the robot. Even though Broadbent et al. [70] mentioned that some older people may show more negative emotions towards robots, this study reveals that familiarity may not necessarily improve the trust index. However, if the robot constantly informs the user on its capabilities, this could have some influence on the users' willingness to trust the capabilities of the robot as observed in [69]. It also brings an important consideration regarding feedback design to the fore: informing users of the capabilities of the robot and demonstrating such capabilities. This form of communicative attribute coupled with reliable performance of the robot as emphasized by Hancock et al. [71] in their study of factors influencing trust in HRI, can potentially help the users trust the robot better. It may also improve the comfortability trend at all age categories as established in the Almere model [72] showing perceptual influences on acceptance of a robot by older adults.

Gender had also been found in previous studies to have a significant influence on the interaction with the robot [67, 69, 73]. This was confirmed in the current study where the females were more engaged to the robot than the males and also seemed to ask more questions to clarify their understanding of the robot better. The females also seemed to trust the robot more as seen in the time they waited for the robot. They seem to trust that the robot would perform correctly even when it delayed or lost track. Even though, Heerink [72] and de Graff [73] associated anxiety with the females' interaction with a robot, the current study agrees with earlier findings by Shibata et al. [74] where it was stated that females are more comfortable around robots. This could potentially influence trust positively. Several reasons could be responsible for this disparity which includes context and type of robot. However, the reason cannot be fully established from this study due to the limited sample. But it highlights the need to further explore the expectations and needs of the different genders such that the feedback design could be tuned to meet possible gender preferences.

Gender and age category of the older adult users should therefore be adequately considered in order to meet the specific needs in the different groups that make up the older adults' population.

8.6 Design implications, limitations and future work

While evaluating the effectiveness of the feedback design, we observed that the users were more engaged with the robot, understood the robot more, and better trusted the robot when it communicated with them using the implemented feedback. This confirms hypotheses *H1 – H3*. Even though analyses of the objective measures did not confirm hypothesis *H4*, the responses of the participants in the questionnaires showed that they were more comfortable communicating with the robot when the feedback was implemented. The feedback was designed to match the perceptual demands of the target users. The outcome supports the proposition in literature that such ***user-centered feedback design can increase the quality of interaction***.

One of the limitations of this study is that the feedback design was evaluated for a single task scenario. The feedback was not evaluated in multiple task situations with varying environmental variables such as noise and space type. Evaluation of the feedback design parameters is also recommended for an extended period of time in order to assess the preferences of the older adults as the novelty effect wears off. It is also recommended that training be conducted for older adult users as naïve users, regarding how the feedback interfaces operate in order to maximize the interaction quality. These are crucial factors that should be considered in future work to improve the robustness of the feedback design. The outcome of this study provides some guidelines and recommendations that could be useful while conducting more extensive studies on feedback design in person-following robots that will accommodate user needs in eldercare. Ongoing research is aimed to advance these studies to other tasks, robot types and populations.

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References

[1] D. Tang, B. Yusuf, J. Botzheim, N. Kubota, and C. S. Chan, "A novel multimodal communication framework using robot partner for aging population," *Expert Syst. Appl.*, vol. 42, no. 9, pp. 4540–4555, 2015.

[2] S. S. Honig, T. Oron-Gilad, H. Zaichyk, V. Sarne-Fleischmann, S. Olatunji, and Y. Edan, "Toward socially aware person-following robots," *IEEE Trans. Cogn. Dev. Syst.*, vol. 10, no. 4, pp. 936–954, 2018.

[3] H. Sidenbladh, D. Kragic, and H. I. Christensen, "A person following behaviour for a mobile robot," in *Proceedings 1999 IEEE International Conference on Robotics and Automation (Cat. No. 99CH36288C)*, IEEE, vol. 1, pp. 670–675, 1999.

[4] S. S. Honig, D. Katz, T. Oron-Gilad, and Y. Edan, "The influence of following angle on performance metrics of a human-following robot," in *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)* (New York, USA), IEEE, pp. 593–598, 2016.

[5] S. Olatunji, V. Sarne-Fleischmann, S. S. Honig, T. Oron-Gilad, and Y. Edan, "Feedback design to improve interaction of person-following robots for older adults," 2018. Available: https://pdfs.semanticscholar.org/2e1e/e201a1de05885e102b0fbdc5dabefefd5531.pdf.

[6] S. Bensch, A. Jevtić, and T. Hellström, "On interaction quality in human-robot interaction," in *Proc. 9th Int. Conf. Agents Artif. Intell. ICAART* (Porto, Portugal), vol. 1, pp. 182–189, 2017.

[7] O. Zafrani and G. Nimrod, "Towards a holistic approach to studying human-robot interaction in later life," *Gerontologist*, vol. 59, no. 1, pp. e26–e36, January 2019.

[8] C. Owsley and G. McGwin Jr., "Association between visual attention and mobility in older adults," *J. Am. Geriatr. Soc.*, vol. 52, no. 11, pp. 1901–1906, November 2004.

[9] I. Leite, C. Martinho, and A. Paiva, "Social robots for long-term interaction: a survey," *Int. J. Soc. Robot.*, vol. 5, no. 2, pp. 291–308, 2013.

[10] European Committee for Standardization, Cen and European Committee for Electrotechnical Standardization, Cenelec, "Guidelines for standards developers to address the needs of older persons and persons with disabilities," *Eur. Comm. Stand. Eur. Comm. Electrotech. Stand.*, vol. 6, no. 2, pp. 1–31, 2002.

[11] T. L. Mitzner, C.-A. Smarr, W. A. Rogers, and A. D. Fisk, "Adult's perceptual abilities," in *The Cambridge Handbook of Applied Perception Research*, pp. 1051–1079, 2015.

[12] E. Claude, "Shannon. Communication theory of secrecy systems," *Bell Syst. Tech. J.*, vol. 28, no. 4, pp. 656–715, 1949.

[13] D. Doran, S. Schulz, and T. R. Besold, "What does explainable AI really mean? A new conceptualization of perspectives," arXiv:1710.00794, 2017.

[14] N. Balfe, S. Sharples, and J. R. Wilson, "Wilson. Understanding is key: An analysis of factors pertaining to trust in a real-world automation system," *Hum. Factors*, vol. 60, no. 4, pp. 477–495, June 2018.

[15] T. Hellström and S. Bensch, "Understandable robots-what, why, and how," *Paladyn, J. Behav. Robot.*, vol. 9, no. 1, pp. 110–123, 2018.

[16] S. Olatunji, T. Oron-Gilad, and Y. Edan, "Increasing the understanding between a dining table robot assistant and the user," in *Proceedings of the The International PhD Conference on Safe and Social Robotics (SSR-2018)* (Madrid, Spain), EU Horizon2020 projects – SOCRATES and SECURE, 2018.

[17] N. Mirnig and M. Tscheligi, "Comprehension, Coherence and Consistency: Essentials of Robot Feedback," in *Robots that Talk and Listen. Technology and Social Impact*, J. A. Markowitz (ed.), De Gruyter, 2014, pp. 149–171.

[18] J. Y. C. Chen, S. G. Lakhmani, K. Stowers, A. R. Selkowitz, J. L. Wright, and M. Barnes, "Situation awareness-based agent transparency and human autonomy teaming effectiveness," *Theor. Issues Ergon. Sci.*, vol. 19, no. 3, pp. 259–282, 2018.

[19] N. Mirnig, A. Weiss, and M. Tscheligi, "A communication structure for human-robot itinerary requests," in *Proc. 6th Int. Conf. Human Robot Interaction* (Lausanne, Switzerland), ACM, 2011, pp. 205–206.

[20] J. B Lyons, "Being transparent about transparency: A model for human-robot interaction," in *2013 AAAI Spring Symposium Series*, Stanford University, USA, 2013.

[21] J. Y. Chen, K. Procci, M. Boyce, J. Wright, A. Garcia, and M. Barnes, "Situation awareness-based agent transparency," *Technical report, Army research lab Aberdeen proving ground MD human research and engineering...*, 2014.

[22] M. R. Endsley, "Toward a theory of situation awareness in dynamic systems: situation awareness," *Human Factors*, vol. 37, no. 1, pp. 32–64, March 1995.

[23] M. Cristani, G. Paggetti, A. Vinciarelli, L. Bazzani, G. Menegaz, and V. Murino, "Towards computational proxemics: Inferring social relations from interpersonal distances," in *2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing* (Boston, MA), IEEE, 2011, pp. 290–297.

[24] A. Theodorou, R. H. Wortham, and J. J. Bryson, "Designing and implementing transparency for real time inspection of autonomous robots," *Connect. Sci.*, vol. 29, no. 3, pp. 230–241, 2017.

[25] T. Inagaki, "Smart collaboration between humans and machines based on mutual understanding," *Annu. Rev. Contr.*, vol. 32, no. 2, pp. 253–261, 2008.

[26] R. Parasuraman, T. B. Sheridan, and C. D. Wickens, "A model for types and levels of human interaction with automation," *IEEE Trans. Syst. Man Cybern. A Syst. Hum.*, vol. 30, no. 3, pp. 286–297, May 2000.

[27] R. H. Wortham and A. Theodorou, "Robot transparency, trust and utility," *Connect. Sci.*, vol. 29, no. 3, pp. 242–248, 2017.

[28] T. Fong, N. Cabrol, C. Thorpe, and C. Baur, "A personal user interface for collaborative human-robot exploration," in *6th International Symposium on Artificial Intelligence, Robotics, and Automation in Space (iSAIRAS)* (Montreal, Canada), 2001.

[29] A. Eliav, T. Lavie, Y. Parmet, H. Stern, and Y. Edan, "Advanced methods for displays and remote control of robots," *Appl. Ergon.*, vol. 42, no. 6, pp. 820–829, November 2011.

[30] N. Markfeld, "Feedback design for older adults in robot assisted table setting task," Master's thesis, Industrial Engineering and Management, Ben-Gurion University of the Negev, Beer Sheva, 2019.

[31] C. Breazeal, C. D. Kidd, A. L. Thomaz, G. Hoffman, and M. Berlin, "Effects of nonverbal communication on efficiency and robustness in human-robot teamwork," in *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems* (Alberta, Canada), IEEE, 2005, pp. 708–713.

[32] T. L. Sanders, T. Wixon, K. E. Schafer, J. Y. C. Chen, and P. A. Hancock, "The influence of modality and transparency on trust in human-robot interaction," in *2014 IEEE International Inter-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)* (Las Vegas, NV, USA), IEEE, 2014, pp. 156–159.

[33] V. Finomore, K. Satterfield, A. Sitz, C. Castle, G. Funke, T. Shaw, and M. Funke, "Effects of the multi-modal communication tool on communication and change detection for command and control operators," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Boston, MA, USA), SAGE Publications Sage CA: Los Angeles, CA, 2012, vol. 56, pp. 1461–1465.

[34] T. Kim and P. Hinds," Who should I blame? Effects of autonomy and transparency on attributions in human-robot interaction," in *ROMAN 2006-The 15th IEEE International Symposium on Robot and Human Interactive Communication*, IEEE, 2006, pp. 80–85.

[35] E. A. Cring and A. G. Lenfestey, "Architecting human operator trust in automation to improve system effectiveness in multiple unmanned aerial vehicles (UAV) control," *Technical report, Air Force Inst. of Tech. Wright-Patterson AFB OH Graduate School of...*, 2009.

[36] G. Doisy, J. Meyer, and Y. Edan, "The impact of human–robot interface design on the use of a learning robot system," *IEEE Trans. Hum. Mach. Syst.*, vol. 44, no. 6, pp. 788–795, 2014.

[37] K. Fischer, K. Lohan, J. Saunders, C. Nehaniv, B. Wrede, and K. Rohlfing, "The impact of the contingency of robot feedback on HRI," in *2013 International Conference on Collaboration Technologies and Systems (CTS)* (San Diego, CA, USA), IEEE, 2013, pp. 210–217.

[38] S. Agrawal and H. Yanco, "Feedback methods in HRI: Studying their effect on real-time trust and operator workload," in *Companion of the 2018 ACM/IEEE International Conference on Human-Robot Interaction* (Chicago, IL, USA), ACM, 2018, pp. 49–50.

[39] J. Hoecherl, M. Schmargendorf, B. Wrede, and T. Schlegl, "User-centered design of multimodal robot feedback for cobots of human-robot working cells in industrial production contexts," in *ISR 2018; 50th International Symposium on Robotics* (Munich, Germany), VDE, 2018, pp. 1–8.

[40] M. R. Endsley and D. B. Kaber, "Level of automation effects on performance, situation awareness and workload in a dynamic control task," *Ergonomics*, vol. 42, no. 3, pp. 462–492, March 1999.

[41] H. Zender, P. Jensfelt, and G.-J. M. Kruijff, "Human-and situation-aware people following," in *RO-MAN 2007 – The 16th IEEE International Symposium on Robot and Human Interactive Communication* (Jeju Island, Korea), IEEE, 2007, pp. 1131–1136.

[42] R. Gockley, J. Forlizzi, and R. Simmons, "Natural person-following behavior for social robots," in *Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction* (Arlington, Virginia, USA), ACM, 2007, pp. 17–24.

[43] H.-M. Gross, A. Scheidig, K. Debes, E. Einhorn, M. Eisenbach, S. Mueller, et al., "Roreas: Robot coach for walking and orientation training in clinical post-stroke rehabilitation – prototype implementation and evaluation in field trials," *Auton. Robots*, vol. 41, no. 3, pp. 679–698, 2017.

[44] S. J. Czaja, W. R. Boot, N. Charness, and W. A. Rogers, *Designing for Older Adults: Principles and Creative Human Factors Approaches*, CRC press, 2019.

[45] M. Quigley, B. Gerkey, and W. D. Smart, *Programming Robots with ROS: a practical introduction to the Robot Operating System*, O'Reilly Media, Inc., 2015.

[46] M. Munaro, A. Horn, R. Illum, J. Burke, and R. B. Rusu, "OpenPTrack: people tracking for heterogeneous networks of color-depth cameras," in *IAS-13 Workshop Proceedings: 1st Intl. Workshop on 3D Robot Perception with Point Cloud Library* (Padova, Italy), 2014, pp. 235–247.

[47] M. Munaro and E. Menegatti, "Fast rgb-d people tracking for service robots," *Auton. Robots*, vol. 37, no. 3, pp. 227–242, 2014.

[48] G. Doisy, A. Jevtic, E. Lucet, and Y. Edan, "Adaptive person-following algorithm based on depth images and mapping," in *Proc. of the IROS Workshop on Robot Motion Planning* (Vilamoura, Algarve, Portugal), 2012, vol. 20, no. 12.

[49] C. Piezzo and K. Suzuki, "Feasibility study of a socially assistive humanoid robot for guiding elderly individuals during walking," *Future Internet*, vol. 9, no. 3, art. 30, 2017.

[50] J. Miura, J. Satake, M. Chiba, Y. Ishikawa, K. Kitajima, and H. Masuzawa, "Development of a person following robot and its experimental evaluation," in *Proceedings of the 11th International Conference on Intelligent Autonomous Systems* (Ottawa, Canada), 2010, pp. 89–98.

[51] C. Bassani, A. Scalmato, F. Mastrogiovanni, and A. Sgorbissa, "Towards an integrated and human friendly path following and obstacle avoidance behaviour for robots," in *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)* (New York, USA), IEEE, 2016, pp. 599–605.

[52] D. Katz, "Development of algorithms for a human following robot equipped with kinect vision and laser sensors in an unknown indoor environment with obstacles and corners," Master's thesis, Industrial Engineering and Management, Ben-Gurion University of the Negev, Beer Sheva, 2016.

[53] M. Ratchford and M. Barnhart, "Development and validation of the technology adoption propensity (tap) index," *J. Bus. Res.*, vol. 65, no. 8, pp. 1209–1215, 2012.

[54] D. S. Syrdal, K. Dautenhahn, K. L. Koay, and M. L. Walters, "The negative attitudes towards robots scale and reactions to robot behaviour in a live human-robot interaction study," *Adaptive and Emergent Behaviour and Complex Systems*, 2009.

[55] R. M. Taylor, "Situational awareness rating technique (sart): The development of a tool for aircrew systems design," in *Situational Awareness*, Routledge, 2017, pp. 111–128.

[56] P. Rani, N. Sarkar, C. A. Smith, and L. D Kirby, "Anxiety detecting robotic system – towards implicit human-robot collaboration," *Robotica*, vol. 22, no. 1, pp. 85–95, 2004.

[57] P. Rani, J. Sims, R. Brackin, and N. Sarkar, "Online stress detection using psychophysiological signals for implicit human-robot

cooperation," *Robotica*, vol. 20, no. 6, pp. 673–685, 2002.
[58] N. Mirnig, B. Gonsior, S. Sosnowski, C. Landsiedel, D. Wollherr, A. Weiss, et al., "Feedback guidelines for multimodal human-robot interaction: How should a robot give feedback when asking for directions?" in *2012 IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication* (Paris, France), IEEE, 2012, pp. 533–538.
[59] M. K. Pichora-Fuller, C. E. Johnson, and K. E. J. Roodenburg, "The discrepancy between hearing impairment and handicap in the elderly: Balancing transaction and interaction in conversation," *J. Appl. Commun. Res.*, vol. 26, no. 1, 99–119, 1998.
[60] A. N. Burda, J. A. Scherz, C. F. Hageman, and H. T. Edwards, "Age and understanding speakers with Spanish or Taiwanese accents," *Percept. Mot. Skills*, vol. 97, no. 1, pp. 11–20, August 2003.
[61] A. M. Sabelli, T. Kanda, and N. Hagita, "A conversational robot in an elderly care center: an ethnographic study," in *2011 6th ACM/IEEE International Conference on Human-Robot Interaction (HRI)* (Lausanne, Switzerland), IEEE, 2011, pp. 37–44.
[62] D. Porfirio, A. Sauppé, A. Albarghouthi, and B. Mutlu, "Computational tools for human-robot interaction design," in *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)* (Daegu, Korea), IEEE, 2019, pp. 733–735.
[63] E. C. Grigore, A. Pereira, I. Zhou, D. Wang, and B. Scassellati, "Talk to me: Verbal communication improves perceptions of friendship and social presence in human-robot interaction," in *International Conference on Intelligent Virtual Agents* (Los Angeles, USA), Springer, 2016, pp. 51–63.
[64] A. Taranović, A. Jevtić, and C. Torras, "Adaptable multimodal interaction framework for robot assisted cognitive training," in *Companion of the 2018 ACM/IEEE International Conference on Human-Robot Interaction* (Madrid, Spain), ACM, 2018, pp. 327–328.
[65] N. Doering, S. Poeschl, H.-M. Gross, A. Bley, C. Martin, and H.-J. Boehme, "User-centered design and evaluation of a mobile shopping robot," *Int. J. Soc. Robot.*, vol. 7, no. 2, pp. 203–225, 2015.
[66] C.-S. Lu and C.-S. Yang, "Safety leadership and safety behavior in container terminal operations," *Saf. Sci.*, vol. 48, no. 2, pp. 123–134, 2010.
[67] L. Bishop, A. Van Maris, S. Dogramadzi, and N. Zook, "Social robots: The influence of human and robot characteristics on acceptance," *Paladyn, J. Behav. Robot.*, vol. 10, no. 1, pp. 346–358, January 2019.
[68] S. Šabanović, C. C. Bennett, W.-L. Chang, and L. Huber, "Paro robot affects diverse interaction modalities in group sensory therapy for older adults with dementia," in *2013 IEEE 13th International Conference on Rehabilitation Robotics (ICORR)*, IEEE, 2013, pp. 1–6.
[69] M. Heerink, "Exploring the influence of age, gender, education and computer experience on robot acceptance by older adults," in *Proceedings of the 6th international conference on Human-robot interaction* (New York, NY, USA), ACM, 2011, pp. 147–148.
[70] E. Broadbent, R. Stafford, and B. MacDonald, "Acceptance of healthcare robots for the older population: review and future directions," *Int. J. Soc. Robot.*, vol. 1, no. 4, pp. 319–330, 2009.
[71] P. A. Hancock, D. R. Billings, K. E. Schaefer, J. Y. Chen, E. J. de Visser, and R. Parasuraman, "A meta-analysis of factors affecting trust in human-robot interaction," *Hum. Factors*, vol. 53, no. 5, pp. 517–527, October 2011.
[72] M. Heerink, V. E. Ben Kröse, and B. Wielinga, "Assessing acceptance of assistive social agent technology by older adults: The almere model," *Int. J. Soc. Robot.*, vol. 2, no. 4, pp. 361–375, 2010.
[73] M. M. A. de Graaf, S. Ben Allouch; Maartje MA De Graaf and Somaya Ben Allouch, "Exploring influencing variables for the acceptance of social robots," *Robot. Auton. Syst.*, vol. 61, no. 12, pp. 1476–1486, 2013.
[74] T. Shibata, K. Wada, Y. Ikeda, and S. Šabanović, "Cross-cultural studies on subjective evaluation of a seal robot," *Adv. Robot.*, vol. 23, no. 4, pp. 443–458, 2009.

Chapter 4: Level of automation models - development and evaluation

Part A

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See following pages for publications.

Usability Testing for the Operation of a Mobile Robotic Telepresence System by Older Adults

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Mobile robotic telepresence (MRP) systems feature a video conferencing interface on a mobile robot, enabling pilot users to remotely control the robot while communicating with a local user. For older adults in an assisted living facility, the operators are mostly caregivers or remote family members. This small-sample usability testing aimed to evaluate the use of MRP by the older adult. Participants navigated the robot to locations in the home, e.g., to check if the front-door is closed. Two levels of automation were introduced; assisted teleoperation and autonomous. Observations revealed that the older adults enjoyed the dexterity with which the robot could be teleoperated in the assisted teleoperation mode. Yet, they preferred the operation of the MRP at the autonomous mode where the robot navigated autonomously towards the locations the user indicated. Usability, preference and objective findings raise awareness regarding elder care assistive robot developmental factors. Future experimental plans are discussed.

INTRODUCTION

Typical mobile robotic telepresence (MRP) systems are characterized by a video conferencing interface on a mobile robot. This enables a pilot user to remotely control the robot while communicating with the local user (Kristoffersson, Coradeschi, & Loutfi, 2013). An important application of a MRP system is in the care of older adults for various functions such as health surveillance, social interaction and safeguarding (Beer & Takayama, 2011). Usually, a family member, health care worker, or caregiver for the older adult controls the MRP. However, there may be situations where an older adult living independently may also want to control the robot locally to perform other functions in the home such as assisting in locating items (e.g., looking for their glasses or medication), detection of hazards (e.g., to see if the gas stove or the water heater were turned off), video call someone (e.g a family member, friend or colleague), or merely to relocate the robot or navigate it to its charging station. Most studies involving MRP for older adults have mostly focused on control by secondary users and caregivers (Coradeschi et al., 2013; Orlandini et al., 2016; Shiarlis et al., 2013). User studies to evaluate the usability of MRP control by the older adults are still lacking.

This usability study examines one of the potential uses of a telepresence robot which is detection of hazards in an older adult home. Many older adults are living in potentially hazardous environments (Carter, Campbell, Sanson-Fisher, Redman, & Gillespie, 1997). Home safety can be improved if the potential hazards are detected and proactive measures taken (Mayhorn, Nichols, Rogers, & Fisk, 2010). Research has shown that older adults' understanding and experience with home hazards can provide a wealth of insight that could inform the design of hazard detection and warning systems (Mayhorn et al., 2010). We therefore explore as a test case, the detection of hazards in a home-like environment using an MRP system teleoperated by an older adult.

A major factor to consider when introducing robotic assistance for older adults at home is their preference to maintain a certain level of autonomy as the robot assists them (Smarr et al., 2012). A strategy proposed in the literature to accomplish this balance is through levels of automation (LOA), which involves defining the degree to which the robot would carry out certain functions in its defined role of assisting the user for each specific task. In the case of caregiving, the appropriate LOA is expected to keep older adults active as one of the highlights of independent living for older adults (Olatunji et al., 2019).

A number of short-term evaluations of MRP for eldercare revealed maneuvering challenges and higher workload while manually driving the robot (Cesta, Cortellessa, Orlandini, & Tiberio, 2013; Kiselev & Loutfi, 2012). This spotlighted the driving of the robot as a critical function to apply LOA to, particularly because specific LOA designs that would be suitable, feasible and fitting to the needs of the older adults are still lacking (Vagia, Transeth, & Fjerdingen, 2016). Evaluation of some semi-autonomy features in MRPs to relieve the pilot user from the mental and physical demand of maneuvering the robot have been previously carried out by (Kiselev et al., 2015). This study builds on that by developing specific features for two LOA designs: assisted teleoperation mode and autonomous mode. In the assisted teleoperation mode, the robot supports the user in the process of tele-operating by automatically slowing down when it gets close to obstacles. In the autonomous mode, the user simply selects a target location in the home and the robot autonomously navigates towards it. We explore the usability of these two LOA designs in MRP for older adults at home.

Usability metric of these two modes of operation and user insights were collected from the older adult participants. The outcomes provide preliminary recommendations for design improvements along with detailed experimental plans for more full scale studies. The study reveals an exciting area of development where the older adults are given the opportunity to teleoperate the MRP system at different levels of autonomy.

METHOD

Participants

Four older adult participants (1 Female, 3 Males) aged 66-71, were recruited for the study through snowball sampling. They participated voluntarily in the study. They did not receive any financial compensation for their participation. They spent about 1 hour on the average for the period of the study.

Apparatus

Experimental environment. The study took place in a home-like setup at the Applied Autonomous Sensor Systems, at Örebro University, Sweden, as shown in Figure 1. The home-like environment consisted of a kitchen, living room, bedroom, and a charging area for the robot. Every space in the environment is on a plane level ground with passages for movement as seen in Figure 1. The participant sat in the living room and controlled the robot around the house from the sofa.

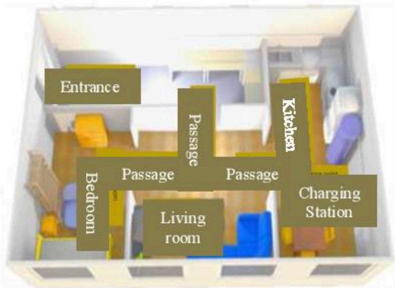


Figure 1. A cross-section of the Örebro University home-like environment used for the study.

User interface. The user interface (as shown in Fig.2) was designed to run on a browser. It could be operated from multiple platforms; personal computers, tablets or mobile phones. It was more convenient for the older adults to use a device that they were already familiar with, which is why a personal computer was used in all trials as the operating platform.

The interface contains three screen sections. The left section contains the video feed of the operator of the robot and controls to adjust the output of the video (e.g. the audio volume could be muted or the image pixelated or blurred). This left section also contains the volume settings for the wide variety of the hearing differences that are common among older people. Below the volume settings are the four conventional navigation arrow-control buttons through which the user can direct the robots to go to a desired direction.

The central section of the interface consists of the video scene as depicted by the robot's camera. A flat-cylindrical shaped pointer with a tail connecting it to the end of the screen. serves as the indicator for a trackball through which the user pointed the robot in the direction they wanted the robot to advance. Clicking on this 'pointing plate' and holding on to the click moved the robot physically in the desired direction. This method of control along with the conventional arrow-control buttons on the left side of the interface described earlier constituted the assisted teleoperation LOA mode.

The right section consists of a robot-generated map of the apartment. This map is a reactive top-down view of the apartment with a dynamic position of the robot represented as it navigates in the environment. It contains some letters to indicate specific sections of the apartment for example 'K' for kitchen, 'L' for living room. The robot is represented as a green dot with an attached smaller red dot to show the direction it is facing. The map was reactive in the sense that the user could click on any part of it and the robot would respond in real time by navigating to the point on the map that was clicked.

The right side of the interface also contains 'goal buttons' which the user could click on to send the robot to a specific location in the apartment (e.g., bedroom, entrance) without the need to give direction or specify a path for the robot. These 'goal buttons' along with the map clicking mechanism served as the autonomous LOA mode.

This user interface was not specifically designed for older adult users, but rather for novice users envisioned to be caregivers who would use the system for various purposes connected with navigating the robot to perform tasks remotely.

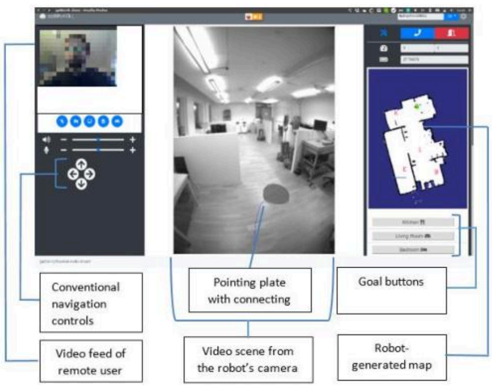


Figure 2. User interface depicting different levels of automation.

The robot

The robot is a mobile robot with a differential drive and a screen for telepresence (shown in Fig. 3). It has with a mechanical tilt but no pan function. A Hokuyo URG-04LX-UG01 Scanning Laser Rangefinder is attached to the base of the robot for navigation. A Structure Core RGBD camera is fitted to the top of the screen for wide angle viewing. The robot runs standard ROS Melodic with an Arduino-based motor driver.

Implementation of LOA

The MRP system was programmed to operate at two levels of automation.

Assisted Teleoperation mode. In this mode, the movement of the robot is teleoperated using the mouse-controlled pointing plate as a steering on the user interface. Another teleoperation option provided in this mode was the convention direction control keys (left, right, forward, backward) was also provided. The robot was programmed to slow down when close to obstacles to ease maneuvering around obstacles.

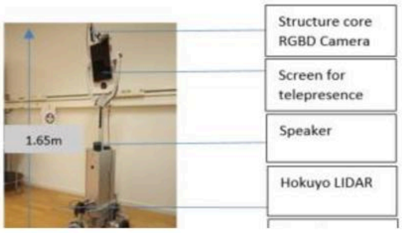


Figure 3. The telepresence robot used for the study.

Autonomous Operation mode. In this mode, controls are provided for the user to give the robot a target location, and then the robot autonomously navigates to it. This was implemented through buttons on the bottom right part of the user interface that bore the names of the goals (such as 'kitchen', 'living room'). It was also possible to click on the point of interest on the map and the robot would autonomously navigate to the point.

Experimental Design and Measures

A within-participants experimental design was used. The independent variables were the levels of automation: Assisted teleoperation mode (A) and Autonomous operation mode (B).

The dependent variable was the perceived usability of the system. Performance measures were the number of sub-tasks successfully completed, the number of hazardous objects identified, the number of correct locations of the identified items, number of errors made in form of collisions with walls or obstacles.

Questionnaires. A demographic questionnaire and an abridged version of the Negative Attitude toward Robots Scale (NARS) questionnaire (Syrdal, Dautenhahn, Koay, & Walters, 2009) were administered at the beginning of the experiment. A simple usability evaluation (as described by the Nielsen-Norman Group for a sample population, (Laubheimer, 2018)) was carried out using Likert scale questions to assess perceived usability in terms of learnability, comfortability, utility, enjoyment and perceived safety of interaction was administered at the end of each trial. A Single ease questionnaire (SEQ) (Sauro, 2012) as a subjective assessment of the ease of use was also administered to the participants at the end of the session.

Task

The task was to navigate the robot from the living room to different parts of the home to carry out five subtasks: 1) if the charging station of the robot is in the bedroom; 2) if the front door is closed; 3) if there were any fall-risk items lying on the floor along the way (e.g., a loose hanging cable on the floor); 4) if the cooker was turned off, and 5) if the tap is running in the kitchen. The order of the sub-tasks varied among the participants and between conditions.

Procedure

Participants participated one at a time during the study. An overview of the experiment was explained to them before they signed the consent form. Background information such as age, gender and occupation of the user was collected. The initial attitude of participants towards technology was collected using NARS. A short training was conducted for the participants to help them understand how to operate the robot through the interface in each of the LOA modes. The task, (described above) was explained to the participants.

The participants carried out the task while sitting in the living room of the model home described in the *experimental environment* section. They operated the robot through the user interface of the system. Upon completion they were asked to navigate the robot back to the charging area. The participants were asked to verbally note their observations and the hazards they detected (e.g., the cooker is turned off, there an item that can cause a fall in the bedroom), while the experimenter took notes. Participants performed this set of tasks twice, once in each LOA mode. The target potential hazard items were changed within trials for the participants without the knowledge of the participant. At the end of each task they filled the post-task questionnaire which was the usability assessment. After completion of the entire session, they filled a post-test questionnaire where they indicated their experience while controlling the robot. At the end of the experiment, they were debriefed regarding the objective of the research and the conditions being tested.

RESULTS

The results present the perception, responses and preference of the users in terms of usability, learnability, ease of use of the system as a whole, particularly for older adult users. The first section of the result presents the demographics of the participants and their predisposition towards the robot as revealed by the outcome of the shortened NARS questionnaire. Further discussion with the participants and their opinion regarding the potential use of the system are also presented.

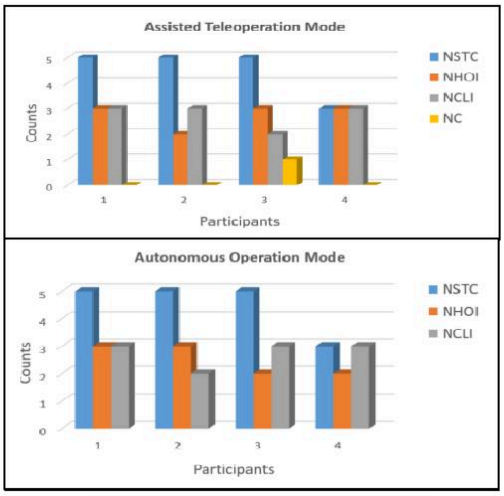
Participants' Demographic Characteristics

The participants were from varying professional backgrounds (2 in teaching, 1 in medicine and 1 in computer systems development). Their predisposition towards the interaction with the robot as revealed by the outcome of the abridged NARS assessment is presented on a scale of 1 to 5 depicting strongly disagree to strongly agree respectively: Anxiety towards the use of the robot (Mdn = 2.5), tension while communicating with a robot (Mdn = 2), shyness if given a job to use robots (Mdn = 3), emotional vulnerability with robots (Mdn = 3), dependability on robots (Mdn = 2).

Objective Performance

Performance measures taken to obtain objective performance of the participants were the number of sub-tasks successfully completed (5 in total), the number of hazardous objects identified (3 in total), the number of correct locations of the identified items, number of collisions of the robot while being teleoperated (this was assessed only in the assisted teleoperated mode where the users had the responsibility of navigating the robot manually without the robot's autonomous navigation).

Three out of the 4 participants successfully completed their tasks without collisions. Only one of the participants collided with the wall in one occasion while tele-operating the robot in the assisted teleoperated mode. Most of the participants spotted the hazardous objects around the home correctly while tele-operating in both modes. The result based on the objective performance of the participants in both LOA modes are presented in Fig.4.



NSTC: number of sub-tasks successfully completed
NHOI: number of hazardous objects identified
NCLI: number of correct locations of identified items
NC: number of collisions

Figure 4. Results for the objective performance of the participants in the Assisted teleoperation (A) and Autonomous operation (B) modes.

Perceived Usability

The outcome of the subjective measures taken to assess specific components of perceived usability: ease of use, learnability, comfortability, utility and enjoyment as presented in Fig.5.

Ease of Use and Learnability

Participants considered both modes easy to use in terms of the amount of effort they had to put in to get the system to perform the specified goal. Though, most of the participants noted that the Autonomous operation mode (Mdn=4.5) was easier to use compared to Assisted teleoperation mode (Mdn=4). Participants expressed pleasure and satisfaction at the ease of tele-operating the system with comments such as "I'm pleased that I can easily control the robot', "it's fun to use".

Most of the participants reported that the Autonomous operation mode (Mdn=3) was easier for them to learn compared to the Assisted teleoperation mode (Mdn=1).

Utility and Satisfaction

Participants considered the robot useful in both LOA modes but felt the Autonomous mode (Mdn=4.5) would offer higher utility than the Assisted teleoperation mode (Mdn=4) particularly when they had other concurrent tasks to perform.

Participants indicated that they were more comfortable using Autonomous mode (Mdn=4.5) compared to Assisted teleoperation mode (Mdn=4). There were no differences in the perception of safety of the participants while controlling the robot in both modes. They considered the robot equally safe to use in assisted teleoperation mode (Mdn=4.5) and autonomous mode (Mdn=4.5) though they seemed to enjoy using autonomous mode (Mdn=4.5) to assisted teleoperation (Mdn=4,).

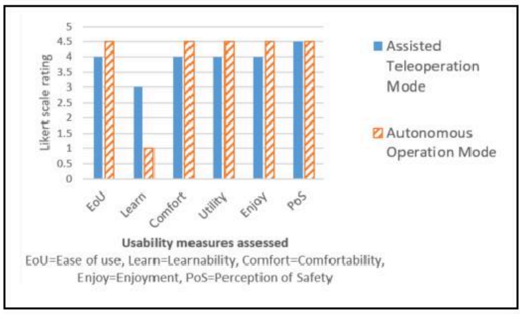


Figure 5. Perceived usability measures by mode of operation.

GENERAL DISCUSSION

This is a small sample usability test study to present the potential of older adults utilizing an MRP system to carry out hazard detection related functions in their home. It provides some insight into the possibility of extending the use and users of such MRP systems to meet the needs of older adult users (Kristoffersson et al., 2013). It forecasts the desired concept of active and successful aging for older adults which involves maintaining mental and physical capacities that facilitate productive and social engagement in society (Rowe & Kahn, 1987).

The developed MRP tested in this study is expected to serve as a tool to aid older adult users perform some needed functions in the home, independently and successfully. It fulfills one of the aims of technology designed for older adult users to aid active aging in terms of engagement in meaningful pursuits for individual wellbeing (Foster & Walker, 2015). Alongside the main use of safety monitoring emphasized in this study, the process of using the system demands a certain level of mental and physical effort from the older adult users that helps them maintain an active and healthy lifestyle threshold. This agrees with the vision of engaging the capabilities of older adults in a way that would contribute to their mental, physical and social wellbeing and improve their quality of life (Alan & Foster, 2013).

Specific levels of autonomy of the robot utilized in the form of LOA modes in the study were employed to explore the effect of such modes on the perceived usability of the system and experience of the older adult users. Results, based on the sample studied, indicate that the older adults were able to effectively accomplish the defined task in both LOA modes. Even though, further discussions with the participants seem to reveal that they can attend to more tasks concurrently if the robot is operating in the autonomous mode. This agrees with literature on the possibility of increasing levels of autonomy to extend users' capabilities (Endsley, 2017). But it is noteworthy that the older adults were able to use the system successfully even in the non-autonomous mode (i.e., assisted teleoperation mode) as revealed by their objective performance and the results from subjective assessment. This highlights the merits of learnability and ease of use of the system in the lower LOA. It also reveals the potential of the older adult users utilizing the system in alternative LOA modes to accomplish specific tasks or subtasks which is one of the objectives of introducing alternative robot autonomy levels (Kaber & Endsley, 1997).

In terms of the resources required to accomplish the task such as time and effort, the system can be described as efficient in both modes for this study. Though, this claim cannot be asserted until further study is carried with more participants and more assessment measures. Duration of the task in this study, for instance was not taken because there were breaks in between the sub-tasks when users discussed their opinion about specific aspect of the system. We would recommend to further assess the efficiency of the system in terms of the resources demanded of the user in relation to extent of task accomplishment using the system (ISO, 2018).

In terms of satisfaction, the results from variables assessed such as comfortability, perception of safety and enjoyment indicate positive responses from the participants. This points to the potential of achieving positive physical, cognitive and emotional responses from the users while using the system in both modes. This is particularly striking, considering the initial disposition of the participants towards the robot that was not clearly positive as indicated by the NARS result.

We acknowledge the limitation of drawing inferences based on the convenience sample of participants, but the study has served to highlight the need for further exploration of the use of MRP systems by older adults to improve their quality of life. It calls for an extended usability study in test environments and also in real homes of older adults. This would better establish the potential of the MRP system to be used by older adults to meet relevant needs and support their independence.

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References

Alan, W., & Foster, L. (2013). Active ageing: Rhetoric, theory and practice. The making of ageing policy. *Edward Elgar Publishing*.

Beer, J. M., & Takayama, L. (2011). Mobile remote presence systems for older adults: Acceptance, benefits, and concerns. In *HRI 2011 - Proceedings of the 6th ACM/IEEE International Conference on Human-Robot Interaction* (pp. 19–26). https://doi.org/10.1145/1957656.1957665

Carter, S. E., Campbell, E. M., Sanson-Fisher, R. W., Redman, S., & Gillespie, W. J. (1997). Environmental hazards in the homes of older people | Age and Ageing | Oxford Academic. *Age and Ageing*, *26*(3), 195–202. https://doi.org/https://doi.org/10.1093/ageing/26.3.195

Cesta, A., Cortellessa, G., Orlandini, A., & Tiberio, L. (2013). Evaluating telepresence robots in the field. *Communications in Computer and Information Science*, *358*, 433–448. https://doi.org/10.1007/978-3-642-36907-0_29

Coradeschi, S., Cesta, A., Cortellessa, G., Coraci, L., Gonzalez, J., Karlsson, L., … Otslund, B. (2013). GiraffPlus: Combining social interaction and long term monitoring for promoting independent living. *2013 6th International Conference on Human System Interactions, HSI 2013*, 578–585. https://doi.org/10.1109/HSI.2013.6577883

Endsley, M. R. (2017). From Here to Autonomy. *Human Factors*, *59*(1), 5–27. https://doi.org/10.1177/0018720816681350

Foster, L., & Walker, A. (2015). Active and Successful Aging: A European Policy Perspective. *The Gerontologist, 55*(1). Retrieved from https://doi.org/10.1093/geront/gnu028

ISO. (2018). *ISO 9241-11:2018(en), Ergonomics of human-system interaction — Part 11: Usability: Definitions and concepts*. Retrieved from https://www.iso.org/obp/ui/#iso:std:iso:9241:-11:ed-2:v1:en

Kaber, D., & Endsley, M. R. (1997). Out-of-the-loop performance problems and the use of intermediate levels of automation for improved control system functioning and safety. *Wiley Online Library - American Institute of Chemical Engineers*, *16*(3), 126–131.

Kiselev, A., Kristoffersson, A., Melendez, F., Galindo, C., Loutfi, A., Gonzalez-Jimenez, J., & Coradeschi, S. (2015). Evaluation of using semi-autonomy features in mobile robotic telepresence systems. *Proceedings of the 2015 7th IEEE International Conference on Cybernetics and Intelligent Systems, CIS 2015 and Robotics, Automation and Mechatronics, RAM 2015*, (ii), 147–152. https://doi.org/10.1109/ICCIS.2015.7274564

Kiselev, A., & Loutfi, A. (2012). Using a Mental Workload Index as a Measure of Usability of a User Interface for Social Robotic Telepresence. *Ro-Man Workshop on Social Robotic Telepresence*, 3–6.

Kristoffersson, A., Coradeschi, S., & Loutfi, A. (2013). A review of mobile robotic telepresence. *Advances in Human-Computer Interaction, 2013*(3), 17. Retrieved from https://dl.acm.org/citation.cfm?id=2514036

Laubheimer, P. (2018). Nielson Norman Group.

Mayhorn, C. B., Nichols, T. A., Rogers, W. A., & Fisk, A. D. (2010). Injury Control and Safety Promotion Hazards in the home: using older adults' perceptions to inform warning design. https://doi.org/10.1080/156609704/233/327497

Olatunji, S., Markfeld, N., Gutman, D., Givati, S., Sarne-Fleischmann, V., Oron-Gilad, T., & Edan, Y. (2019). Improving the interaction of Older Adults with Socially Assistive Robots for Table setting. In *Eleventh International Conference on Social Robotics (ICSR 2019)*. Madrid, Spain.

Orlandini, A., Kristoffersson, A., Almquist, L., Björkman, P., Cortellessa, G., Galindo, C., … Nilsson, M. (2016). ExCITE Project: A Review of Forty-two Months of Robotic Telepresence Technology Evolution. *MIT Press Journal - Presence: Teleoperators and Virtual Environments*, *25*(3), 204–221.

Rowe, J. W., & Kahn, R. L. (1987). Human aging: Usual and successful. *Science*, *237*(4811), 143–149. https://doi.org/10.1126/science.3299702

Sauro. (2012). *10 things to know about the Single Ease Question (SEQ). Measuring U.*

Shiarlis, K., Messias, J., Van Someren, M., Whiteson, S., Kim, J., Vroon, J., … Michel, H. (2013). TERESA: A Socially Intelligent Semi-autonomous Telepresence System. In *6th International Conference on Human System Interactions (HSI)*. Retrieved from http://www.teresaproject.eu

Smarr, C. A., Prakash, A., Beer, J. M., Mitzner, T. L., Kemp, C. C., & Rogers, W. A. (2012). Older adults' preferences for and acceptance of robot assistance for everyday living tasks. *Proceedings of the Human Factors and Ergonomics Society*. https://doi.org/10.1177/1071181312561009

Syrdal, D. S., Dautenhahn, K., Koay, K., & Walters, M. L. (2009). The negative attitudes towards robots scale and reactions to robot behaviour in a live human-robot interaction study. *23rd Convention of the Society for the Study of Artificiel Intelligence and Simulation of Behaviour, AISB*, 109–115. https://doi.org/10.1.1.159.9791

Vagia, M., Transeth, A. A., & Fjerdingen, S. A. (2016). A literature review on the levels of automation during the years. What are the different taxonomies that have been proposed? *Applied Ergonomics*, *53*, 190–202. https://doi.org/10.1016/j.apergo.2015.09.013

Levels of Automation for a Mobile Robot Teleoperated by a Caregiver

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Caregivers in eldercare can benefit from telepresence robots that allow them to perform a variety of tasks remotely. In order for such robots to be operated effectively and efficiently by non-technical users, it is important to examine if and how the robotic system's level of automation (LOA) impacts their performance. The objective of this work was to develop suitable LOA modes for a mobile robotic telepresence (MRP) system for eldercare and assess their influence on users' performance, workload, awareness of the environment and usability at two different levels of task complexity. For this purpose, two LOA modes were implemented on the MRP platform: assisted teleoperation (low LOA mode) and autonomous navigation (high LOA mode). The system was evaluated in a user study with 20 participants, who, in the role of the caregiver, navigated the robot through a home-like environment to perform various control and perception tasks. Results revealed that performance improved at high LOA when the task complexity was low. However, when task complexity increased, lower LOA improved performance. This opposite trend was also observed in the results for workload and situation awareness. We discuss the results in terms of the LOAs' impact on users' attitude towards automation and implications on usability.

CCS Concepts: • Computer systems organization → Robotic autonomy; *External interfaces for robotics*.

Additional Key Words and Phrases: Mobile Robotic Telepresence, Eldercare, Levels of Automation

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1 INTRODUCTION

Many older adults prefer aging in place within their own homes, which has been associated with increased wellbeing [38]. Moreover, as the ratio between the aging population and caregivers continually increases [37] and families live farther apart, this circumstance often becomes a necessity. Although many older adults manage to remain largely independent, they may require occasional help with activities of daily living from a nurse or family member. This can be facilitated through the use of mobile robotic telepresence (MRP) systems [23]. MRP refers to the activity of remote controlling a robot that is able to move through its environment, enabling their users (referred to as remote user or operator) to interact with other people (local users) within that same physical space [23]. As robotic hardware keeps evolving and sophisticated sensors and actuators become affordable, users will be enabled to perform more complex tasks – for example, as in the present use case, to support older adults in their daily lives [28] or when social distancing is required [15]. In the future, caregivers who cannot be physically present in the older adult's residence will be able to use telepresence robots to visit. These systems afford a high level of independence and wide range of action, as seen in several projects focusing on the development of telepresence robots to support older adults in a range of daily activities [50]. Examples of previous work include developing a research platform (GiraffPlus [9]), design recommendations and functionalities (ExCITE EU project [31]), and developing social navigation capabilities (the TERESA project [41]). The present study focuses on two specific constructs, levels of automation (LOA) and task complexity, which were evaluated in terms of performance, workload, SA and usability.

LOA defines the degree to which automation is employed in a given task [1, 13, 27]. The decision to focus the LOA design on navigation is due to several short-term evaluations of MRP for telecare in home environments which revealed maneuvering challenges and higher workload while manually driving the robot [8, 22]. If navigation is automated efficiently, it can allow the operator to direct their attention to other tasks and subtasks. [34]. Furthermore, as tasks become increasingly complex, it may be difficult for an operator to conduct the task sufficiently well manually [10]. Therefore, navigation is a critical function for which LOA can be introduced, especially in the context of different levels of task complexity.

Situation awareness is described as the degree to which operators, at any point in time while controlling or monitoring a system (e.g., a robot), are aware of its current state and the state of the environment in which it is located and acting. In the literature SA is defined as a qualitatively incremental variable spanning three levels: The ability to perceive the incoming and available data that is relevant to the current task or context, understanding the meaning and implications of that data as it pertains to the current state, and finally the ability to make predictions about how the situation is likely to develop in the (near) future if kept on its current trajectory [12]. Mental workload is a measure of the degree to which a person's executive cognitive functions are being occupied at a given time [6], for example as a result of focusing on one or several tasks which demand sustained allocation of these processes.

Task complexity has been identified in previous research as a critical factor influencing the LOA design in humanrobot interaction [1, 17] and impacting performance [10]. Task complexity depends predominantly on properties of the task (objective complexity) and the perception of the human operator (subjective complexity) [36]. Further dimensions of complexity include *component complexity* – the number of distinct actions that the human operator must execute or number of informational cues that should be processed (e.g., the number and types of subtasks to be managed individually) [29]; *coordinative complexity* – the nature of relationships between task inputs and task products, the strength of these relationships, simultaneous action requirements, as well as the sequencing of inputs (e.g., timing, frequency, intensity and location requirements, level of difficulty) [7] and *dynamic complexity* – changes in the states of the environment, e.g., cause-effect chains, means-ends connections to which the human operator should adapt, criticality of changes and the degree of human intervention required for these changes [4, 48].

Only few studies have considered task complexity in the design and evaluation of LOA for MRP systems specifically in the case of non-technical operators (e.g., caregivers) [23, 24, 42]. Specific LOA designs suitable and feasible for such MRP scenarios are still lacking [44]. Previous work [21]evaluated semi-autonomy features in MRPs designed to relieve the pilot user of some of the mental and physical demand associated with maneuvering the robot. Other studies revealed that adjusting the robot's autonomy in teleoperation tasks can help facilitate their use across a broader range of applications [19, 40]. In the context of a user interacting with a robot, such as in the case of an MRP task, it has been previously argued that dynamic adaptation of control and responsibilities is necessary to accommodate different users and successfully manage a variety of situations and tasks [35]. Autonomy is typically considered as a continuous or discrete spectrum, with direct human control and full autonomy at either end, and any number of intermediate levels in between [1]. However, this view is arguably more appropriate when considered at the task level, since a system may be performing multiple tasks simultaneously at different levels of autonomy. Moreover, most tasks can be decomposed further into subtasks and basic actions, which may be shared between robot and human operator.

This work's contribution is the development and evaluation of two LOA designs – assisted teleoperation (low LOA) mode and autonomous (high LOA) mode – which are functional, suitable and adaptable for users in different task complexity scenarios. Navigating the robot in a more complex task with longer interactions, more waypoints and obstacles can lead to fatigue or loss of SA, on which the LOA design of the MRP system may have an impact. User attitude towards the LOA designs at different levels of complexity was investigated in a user study.

Participants took on the role of a caregiver controlling a telepresence robot using different LOA modes – to navigate through an assisted living apartment, check in on a person and perform a variety of observational tasks. The study comprised four conditions, combining two independent variables in a factorial format: LOA and task complexity. The objective was to evaluate the influence of the LOA modes on users' performance, workload, SA and usability in a teleoperated task focusing on navigation.

The next section describes the different aspects of the MRP task in the present study, i.e., the functions to be carried out by the user, their respective allocation in the two LOAs, as well as the process of facilitating the coordination of the user-robot interaction. Section 3 provides an in-depth description of the study design and methodology, followed by results, discussion and outlook in sections 4, 5 and 6, respectively.

2 FUNCTION ALLOCATION AND LOA DEVELOPMENT IN MRP

The function allocation and LOA development for the MRP were aimed to ensure that tasks (and subtasks) in the system are appropriately allocated to the human, robot, or both, at specific degrees of autonomy while allowing for adaptation as required under varying conditions. Fully manual and fully autonomous modes were not included in the design. Achieving full autonomous operation is not practical at the moment, as the tasks may change and the systems are still not developed enough to support dynamic changes in the home environment. However, intermediate levels where functions and tasks are shared between the operator and the robot are feasible.

The function allocations are based on estimated capacities of the user and robot in a given situation to ensure coordination and collaboration between the human and the automation [11]. The functions in the MRP system were identified according to the four-stage 'O-O-D-A loop' information model [3, 13, 33]. It involves functions related to 1) information acquisition (*Observe*), 2) information analysis (*Orient*), 3) decision selection (*Decide*) and 4) action implementation (*Act*), for the operation of the robot in the local environment and the remote operator user interface, as shown in Table 1.

Table 1. Functions in the MRP task

System Aspect	Functions at different stages			
	Information Acquisition	Information Analysis	Decision Selection	Action Implementation
Environment	Monitoring the driving environment. Identifying safe paths to navigate. Identifying objects.	Generating positioning and navigation plans.	Selecting optimal and safe paths for navigation.	Executing steering, stopping, accelerating, decelerating.
User interface	Monitoring state of the robot such as network connectivity, battery status, required features on the interface.	Generating options for controlling the robot and for communication.	Selecting the means to control the robot and to communicate.	Activating modes for navigation, and communication.

These functions were utilized in defining two LOA modes, to qualify the MRP system for navigation focused on the specific task of obstacle detection and avoidance (Table 2). In this process, considerations were made regarding possible failures or emergencies. The role of handling such situations is referred to as a 'contingency role' which involves taking certain actions in the light of such events. Details of the roles in each of the LOA modes are described below. Some roles such as monitoring, analysis and selection of multimedia settings and communication are entirely under the operator's control in both modes.

2.1Assisted Teleoperation Mode (Low LOA)

In the low LOA mode, the human observes the environment through a video stream. A map located on the side of the interface displays the robot's position and is continually updated as the robot moves. The human observes the environment to ensure that the robot does not collide with any object or person as it is directed towards a goal. Meanwhile, the robot scans the environment with its laser scanner. If obstacles are detected within a certain range, it decelerates to avoid collision or to attenuate the impact. This is done simultaneously and autonomously, without the need for the human to activate, manipulate or regulate the monitoring process during the task. This mode can be described as a guarded teleoperation mode.

The operator is further in charge of strategy generation and decision making, identifying possible trajectories to reach the chosen destination and managing various multimedia settings related to the social interaction. These actions are jointly executed by the human and the robot. The human takes the action of activating controls related to starting the robot, positioning and navigating the robot through the user interface, but the robot decelerates based on obstacle proximity as reported by its laser readings.

Additionally, it is primarily the human operator's responsibility to monitor the system's state through the user interface, to ensure that essential modules are functioning adequately. The robot only assists partially in monitoring the battery level, setting off a warning sound when it drops below a preset threshold.

2.2Autonomous Navigation Mode (High LOA)

The robot is fully responsible for observing the environment to identify potential obstacles in its path, while the human operator only monitors the state of the robot through the user interface. The autonomous system identifies areas that are safe for navigation and within which the operator can select an appropriate goal location. The autonomous navigation, in turn, plots a viable path, if any can be found, towards the desired destination and subsequently follows it. As the robot moves through the environment, it continuously updates its local map to track dynamic obstacles which it subsequently avoids when and where possible. This differs from the assisted teleoperation mode, where the map is also continuously updated but the robot only decelerates to avoid or minimize collision with obstacles. Throughout this process, the operator can decide to switch between LOA modes or cancel an active goal, as deemed appropriate or necessary. The rationale for allowing participants to switch from the high to the low LOA was that, upon arriving at a location, teleoperation is better suited for fine-tuning, particularly for adjusting the orientation to face areas of interest. While it is possible to do so with the high LOA mode, it may not be quite as precise as desired. We therefore provide the option for switching in this mode.

Table 2. Summary of LOA Modes Implemented for the MRP

LOA Mode	Brief Description	Function Allocation				Cont.	Coord.	Switch
		Observe	Orient	Decide	Act			
Low LOA (Assisted Teleoperation)	Human observes through robot, plans and decides alone but executes with robot.	Human and robot	Human	Human	Human and robot	Human	Human	NA
High LOA (Autonomous navigation)	Robot scans with human but plans navigation alone. Human decides goal but robot decides path.	Robot and human	Robot	Robot and human	Robot and human	Robot and human	Robot and human	Human

Cont=contingency roles for fallback tasks, Coord=coordinating responsibility demands such as in path planning and obstacle avoidance, Switch=LOA switching option

3 METHODOLOGY

3.1 Overview

User studies were conducted at the Center for Applied Autonomous Sensor Systems (AASS) at Örebro University in Sweden. A telepresence robot was deployed in a home-like testbed environment (called 'PEIS-Home 2') with (a living room, kitchen and bedroom) (see Figure 1). The walls separating the rooms are only approximately one meter high, which allows experimenters to keep a view over the entire space. In a separate room outside of view and hearing range of the robot, participants were seated in front of a standard computer screen with a mouse and keyboard to control the robot through a user interface. A social humanoid robot (Pepper robot) [32] was placed in the living room to represent a resident in the home (henceforth referred to as the resident robot). The description of the MRP system used, the LOA modes implemented on the user interface, the tasks and the experimental design are presented in the following subsections.

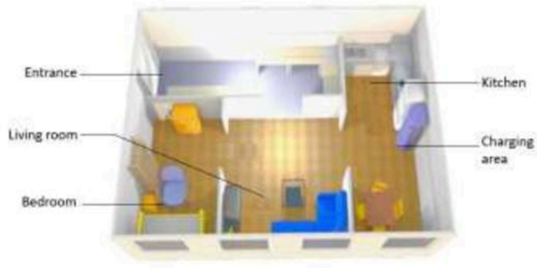

Fig. 1. A cross-section of the home-like environment used for the study.

3.2 The System

The MRP system consists of a mobile robot platform with remote and local user interfaces developed to work through a server-client communication architecture utilizing WebRTC and rosbridge websocket. The user interfaces run within a standard web browser and are independent of the device's operating system or any specific software. This is particularly relevant in the case of the operator client, as it makes the robot more widely accessible and less prone to issues such as missing updates. More details on the robot platform and user interfaces are provided as follows:

The robot platform. The platform is an extensively retrofitted Giraff telepresence robot [31] with a differential drive and screen with mechanical tilt function. Its height is approximately 1.65m and the footprint of the base 0.55 by 0.62m (see Figure 2). The most significant modifications to the original hardware configuration include the removing of the plastic cladding, replacing the battery and adding a Hokuyo URG-04LX-UG01 2D laser scanner, as well as a wide-angle Structure Core RGBD camera. The latter was only used as a RGB webcam. The proprietary software was replaced with a custom-designed interface and back-end implementation based on the robot operating system (ROS). high LOA was realized via the ROS navigation stack, which provides the controller, local and global planners, as well as 2D obstacle detection using the laser range data.

User Interface. The user interface for the local user is displayed on the robot's screen and includes the video stream for the local user to communicate with the remote operator. The remote operator user interface (see Figure 3), is shown on the computer through which the remote operator controls the robot and divided into three sections: a left, central and right panel. The left panel contains the video feed of the operator of the robot, multimedia controls and the four conventional navigation control buttons. The central panel contains the video of the scene overlaid with a trackball-like driving mechanism which is detailed below along with the LOA implementation. The right panel includes a robot-generated reactive map of the apartment and 'goal buttons' to send the robot to specific locations within the home.

The two LOA modes are realized and accessed within this remote operator user interface. In the low LOA mode, the first and main option for navigation control is operated via the trackball-like driving mechanism on the central panel of the interface. This 'pointing plate' indicates the approximate position the robot would move towards, with a curved line originating from the center bottom to plot a rough trajectory towards that site (see Figure 3). If the mouse is moved across the central part of the interface containing the video scene, the plate and tail follow the mouse on a

Fig. 2. The modified Giraff telepresence robot.

plane projection representing the floor. By pressing and holding down the mouse button, users accelerate the robot; releasing the button causes it to slow down and eventually come to a stop. The higher up (and thus farther ahead of the robot) the cursor is on the image while the mouse button is pressed, the faster the robot moves forward. Likewise, the angular velocity increases as the cursor is dragged farther to the left and right edges. This type of interface was chosen because it allows for precision with respect to linear and angular velocity (as opposed to keyboard keys) while relying on the mouse as a commonplace input device. The other, auxiliary navigation control option for the low LOA mode

was the conventional navigation control buttons on the left panel of the interface, i.e., arrows for left, right, forward, and backward in the X-Y plane. This option has been introduced largely as a fallback system for simple actions such as backing up or rotating in place.

In the high LOA mode the user selects the desired goal on the reactive top-down map on the right side of the interface. The map displays the environment used for the study, along with annotations of relevant locations corresponding to specific rooms. By clicking on any accessible location on the map, the robot is given the task to plan a suitable path and navigate towards the destination. Dragging the mouse in any direction before releasing the button determines the orientation the robot is going to rotate towards upon reaching the goal. The secondary navigation control option in the high LOA mode is given through the goal buttons, labeled with the name of the different locations in the environment (e.g. kitchen, living room, bedroom). The user can click on any of these buttons to send the robot to the desired location. Since this option only allows to move to a small set of discrete positions, it is not suited as a standalone function and rather intended to serve as a supporting feature. Nevertheless, both options rely on the same underlying mechanics (i.e., map coordinates and the ROS navigation stack).

Fig. 3. The operator's user interface: the camera image from the robot with the graphical indicator for the manual navigation is in the center, the operator's own webcam, multimedia control buttons, and the conventional navigation buttons are located on the left of the screen; the interactive map and goal buttons are to the right. The same user interface was used for the high and low LOA mode but only specific features corresponding to the LOA in use were allowed for use in each experimental condition

3.3 Tasks

The tasks involved navigating the robot through the environment to specific locations while looking out for certain details in the surroundings. To assess participants' situation awareness, two items were placed on the floor in the doorway and the kitchen. The exact location of the items was randomized across the different trials. The robot always started at its charging station. An observation sheet was provided for the participants to take notes of their observations. Below, we describe the action sequences in both tasks:

Low complexity task (LTask). This task involves a small set of actions and input sequence requirements from the user, contributing to low component and coordinative complexity, respectively. The sequence of actions is as follows: 1. Locate the resident robot in the environment and drive up to it, 2. Communicate with the robot (a short script for the communication was provided), 3. Navigate the robot back to its charging area.

High complexity task (HTask). This task involves a more distinct set of actions, as the user has to carry out longer input sequences. This increases the component and coordinative complexity compared to the low complexity task. The sequence of actions is as follows: 1. Locate the charger of the resident robot, 2. Check if the door to the home is closed, 3. Check for any obstacles on the floor that could cause a fall (two specific objects were placed on the way to the home's entrance door and in the passage to the kitchen), 4. Check if the tap in the kitchen sink is running, 5. Navigate the robot to the charging area, 6. Check if the robot's charger is plugged in.

3.4 Hypotheses

Previous research revealed that performance is more likely to decline at higher robot autonomy with increasing task complexity [10]. Intuitively, it seems plausible to assume that longer and more complex tasks involve a higher potential for the occurrence of dynamic and unforeseen events which may require a degree of flexibility that (current) automation cannot provide. We therefore propose that: *H1: As task complexity increases, user performance will be higher in lower LOA (relative to higher LOA).*

We assume that high task complexity often involves a higher probability of performance declines, uncertainty and failure. Previous research revealed that users appear to have more confidence in their own ability to handle decisions at such higher levels of complexity compared to automation-generated decisions [14]. Increasing automation at high task complexity where more uncertainties can arise often shifts the workload towards monitoring, in an effort to ensure performance, as previously expressed by [2, 47]. This leads to the second hypothesis: *H2: As task complexity increases, workload will increase in high LOA (relative to lower LOA).*

Assessments of SA at different levels of automation [14] revealed that, as automation increases, users' comprehension of the different variables related to the current task declines. This trend appears self-evident, as higher LOA reduces the human involvement, thus allowing operators to direct their attention towards other tasks. This relates to an out-of-the-loop performance problem which has been widely documented as a potential negative consequence of higher LOA [2, 25, 45]. These works mostly examined tasks related to aviation. In the current MRP scenario, which differs considerably with respect to system demands, user expectations and performance assessment, we suggest that: *H3: As task complexity increases, SA will be higher in lower LOA (relative to higher LOA).*

Many of the field studies conducted with MRP systems outlined the need for inclusion of autonomous features to improve the usability of the system and satisfaction [31]. Efforts to introduce MRP platforms to reduce mental demand on users have been reported as being promising [20, 21]. The availability of more autonomous functions may increase users' willingness to use the system when facing increasingly complex tasks. Therefore, we propose that:

H4: As task complexity increases, the availability of LOA options will improve usability.

3.5 Experimental Design

The study was conducted in a within-participants format, with every participant performing a total of four randomized trials corresponding to four different conditions. The conditions resulted from the 2x2 factorial combination of the independent variables, *task complexity (low, high)* and *LOA mode (low, high)*. In the high LOA mode, participants were allowed to switch to low LOA at any point in the task, as they preferred. This is due to the fact that, upon arriving at a location, teleoperation is often better suited for small adjustments to the position and orientation of the robot. These adjustments are frequently made when looking around and inspecting areas of interest.

The dependent variables were *user performance*, *perceived workload*, *situation awareness*, and *usability*, as detailed in Section 3.7.

3.6 Participants

Twenty undergraduate students and researchers (7 female, 13 male) at Örebro University were recruited as participants for the role of the caregiver (*M=29, SD=6*). A majority (14) had a technical background and all reported that they use a computer daily, while most (16) use it at work consistently. Nine stated that they do not play any video games at all, while most of the others play games that may have a positive effect on their understanding of and performance with controlling the robot's interface (e.g., first person shooters, strategy games). All experiments were approved by the ethics review board at Örebro University.

3.7 Procedure

At the start of the experiment, after reading and signing the consent form, participants were asked to provide some background information regarding their age, gender, level of education, field of study/occupation as well as computer use and video gaming experience. Following this, they were briefed on the scenario, tasks and procedure. Before starting with the four main trials, users were introduced to the user interface and had the chance to practice with both operation modes until they felt sufficiently familiarized with the controls. This was defined as *training to a basic use criterion* - to navigate the robot to a specified location and back. Each trial was followed by a questionnaire enquiring about the experience with the condition. In between trials, while participants were occupied with the questionnaires, the experimenters would make subtle changes to the environment to reduce the learning effect. These changes concerned the locations or states of objects relevant to the tasks. After completion of all four trials, participants answered a final questionnaire in which they rated their overall experience with the robot and tasks. It further afforded the opportunity to provide free input, feedback or remarks.

3.8 Measures

3.8.1 Objective Measures. For each participant and trial, performance was measured in terms of task completion time, the number of subtasks completed, and the number of obstacles missed. Additionally, the number of collisions while operating in the low LOA mode was recorded (this was not assessed for the high LOA mode since the function of navigating was performed by the robot with few collisions). Collisions were defined as any contact with walls, furniture or the resident robot, while assuming that all collisions are unintentional. Switching of the LOA mode during task execution in the high LOA condition was also taken into account (frequency and reason for switching).

3.8.2 Subjective Measures. The post-trial questionnaires included a total of 19 questions from three questionnaires as detailed below. The questions were related to perceived workload (rated on a 5-point Likert scale), situation awareness (7-point Likert scale - according to the standard of the Situation Awareness Rating Technique (SART) [43], explained below) and usability (5-point Likert scale, see Table 3). Perceived workload was assessed using the NASA-Task Load Index (NASA-TLX) questionnaire [16], with overall perceived workload rating computed from the different workload dimensions. It has previously been employed in the evaluation of MRP systems [22]. Situation awareness was assessed using the 3D-SART version of the Situation Awareness Rating Technique [43], which measures complexity of interaction, focus of attention and information quantity. Subjective assessment concerning the system's usability was collected by means of the System Usability Scale (SUS) questionnaire [5]. The final questionnaire included participants' assessments regarding the ease of use, as well as possible recommendations for how to develop the system further. Ease of use was evaluated with the Single Ease Questionnaire [39].

3.9 Data Analysis

A generalized linear mixed model (GLMM) was applied to analyze the data with the LOA mode and task complexity as fixed modes, whereas the random effect was selected as the variances from the participants. The tests were designed as two-tailed with a significance level of 0.05.

Table 3. Self-report items from the post-trial questionnaire

Perceived workload (scale 1-5) - NASA-TLX [16] Mental Demand: How mentally demanding was the task? Physical Demand: How physically demanding was the task? Temporal Demand: How hurried or rushed was the pace of the task? Performance: How successful were you in accomplishing what you were asked to do? Effort: How hard did you have to work to accomplish your level of performance? Frustration: How insecure, discouraged, irritated, stressed, and annoyed were you?
System usability (scale 1-5) - SUS [5] I think that I would like to use this system frequently. I found the system unnecessarily complex. I thought the system was easy to use. I think that I would need the support of a technical person to be able to use this system. I thought there was too much inconsistency in this system. I would imagine that most people would learn to use this system very quickly. I found the system very cumbersome to use. I felt very confident using the system. I needed to learn a lot of things before I could get going with this system.
Situation awareness (scale 1-7) - 3D-SART [43] Complexity of Interaction: Is it complex with many interrelated components (High) or is it simple and straightforward (Low)? Focus of Attention: Did you concentrate on many aspects of the interaction (High) or focus on only one (Low)? Information Quantity: How much information have you gained about the environment the robot was navigating in?

4 RESULTS

Objective performance results are presented as a plot in Figure 4, while more details on the interaction effects of LOA and task complexity on the subjective variables are provided in the following subsections:

4.1Objective Performance

Subtasks Completed. In the low complexity task, all except one participant completed the subtasks using the low LOA mode and seventeen out of twenty participants completed the subtasks using the high LOA mode. In the high complexity task 10/20 participants completed the subtasks using low LOA mode while 11/20 participants completed the subtasks using the high LOA mode. In the high LOA mode, 5/20 participants used the map option actively for navigation while about 4/20 participants stayed with the use of the conventional arrow key controls in the low LOA mode (see Figure 4).

Objects Missed. The 'fall risk' object which was placed on the floor in the robot's path was detected by 9 out of 20 participants in the high LOA mode and by 8 out of 20 participants in the low LOA mode in the high complexity task.
One participant in the high LOA mode missed the resident robot in the low complexity task (Figure 4).

Collisions. Three out of twenty participants had collisions with different objects in the environment (mainly with walls, a table and chairs) while navigating using the low LOA mode in the low complexity task and 4/20 participants had a collision in the high complexity task (Figure 4). Though not part of the objective performance assessment, it is worth mentioning that the robot did occasionally collide in the high LOA mode, since its laser scanner only detects obstacles on a 2D plane. Few objects protruding at different heights were not registered. On other rare occasions the robot would rotate in place as a recovery behavior before continuing on to the destination. These incidents may have had an impact on subjective measures such as trust.

Switching of LOA. Twelve out of the twenty participants switched from the high LOA mode to the low LOA mode at an average of 2 times in a run for various reasons detailed in Table 4. Three out of these twelve participants switched in the low complexity task while the other 9 switched in the high complexity task. Six out of the twelve who switched to the low LOA mode returned to the high LOA mode after resolving the situation for which they made the initial switch (Figure 4). The remaining 6 of the 12 who switched to the low LOA mode kept switching between both modes until they completed the task. The reasons for this are also contained in the conditions in

(Figure 4). It should be mentioned that, if participants ended up executing more than 75% of the tasks in the high LOA condition with teleoperation, it was counted as successful completion in low LOA mode. However, if the high LOA condition was only used for looking around and orienting the robot, it was considered as completed in high LOA mode.

4.2Perceived Workload

Mental demand. LOA mode and task complexity had a significant interaction effect on participants' mental demand (*F(1,73)=1.589, p=0.009*). At low task complexity, the low LOA mode placed a higher mental demand (*M=2.00, SD=1.05*) on the participants compared to the high LOA mode (*M=1.53, SD=1.02*). In high task complexity, however, both low LOA mode (*M=2.25, SD=0.97*) and high LOA mode (*M=2.21, SD=1.18*) had an equally high mental demand. The LOA mode alone, however, did not have a significant effect on the mental demand (*F(1,73)=1.910, p=0.171*), though at high task complexity (*M=2.23, SD=1.06*) there was a significantly higher mental demand (*F(1,73)=6.536, p=0.013*) compared to the low task complexity condition (*M=1.76, SD=1.05*)

Table 4. Conditions observed for switching from the high LOA mode to the low LOA mode

Condition for Switching	Examples
Automation transparency	When they were not sure what the robot was doing while it was navigating autonomously
Unexpected events	When the robot got stuck between obstacles and could not get out on its own
Dissatisfaction with the automation	When the robot did not position itself or accelerate as intended, participants switched to the low LOA mode to fine-tune the actions of the robot
Error handling	If participants gave the wrong instruction to the robot and wanted to correct the error
Safety considerations	Some of the participants stated that they were concerned about the robot colliding with obstacles as it navigated on its own
Automation malfunctions	If the robot did not perform as expected in navigating to the desired location.

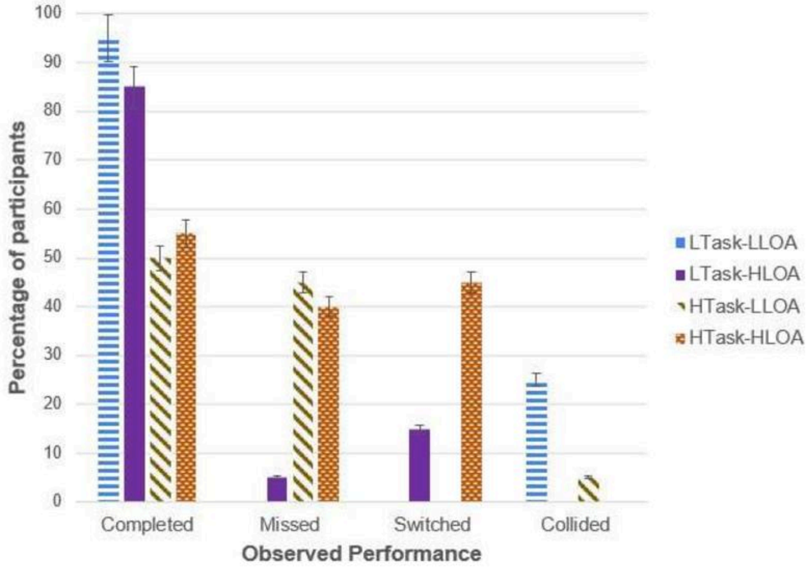

Fig. 4. Performance of the participants in the objective measures
LTask-LLOA = low LOA mode in low task complexity, LTask-HLOA = high LOA mode in low task complexity, HTask-LLOA = low LOA mode in high task complexity, HTask-HLOA = high LOA mode in high task complexity, Completed =Participants who completed all subtasks, Missed = Participants who missed obstacles, Switched = Participants who switched to the low LOA mode while in high LOA mode, Collided = Participants who collided with obstacles in the low LOA mode

Physical demand. The interaction of the LOA mode and task complexity was significant with respect to the physical demand on the participants ($F(1,73)=8.6$, $p=0.004$). Using the low LOA mode was similarly demanding in low task complexity ($M=1.68$, $SD=1.00$) and high task complexity ($M=1.65$, $SD=1.04$). However, while using the high LOA mode, participants reported a lower physical demand in low task complexity ($M=1.16$, $SD=0.38$) compared to the high task complexity ($M=1.79$, $SD=0.98$), where participants reported an increased physical demand. The task complexity as a main effect had a significant influence ($F(1,73)=8.6$, $p=0.047$) on the physical demand in a pattern similar to the mental demand, in that the high complexity task was more physically demanding ($M=1.72$, $SD=0.99$) than the low complexity task ($M=1.42$, $SD=0.79$). Regardless of this, LOA mode as a main effect was not significant in terms of physical demand ($F(1,73)=0.008$, $p=0.930$).

Temporal Demand. The interaction effect of the LOA mode and task complexity was not significant (*$F(1,73)=1.534$, $p=0.219$*), neither was the LOA mode as a main effect (*$F(1,73)=0.383$, $p=0.538$*). The task complexity was significant as a main effect (*$F(1,73)=6.136$, $p=0.016$*). The high complexity task placed a higher temporal demand (*$M=2.05$, $SD=1.12$*) on the participants compared to the low complexity task (*$M=1.63$, $SD=0.85$*).

Operator Performance. Significant interaction was observed between LOA mode and task complexity (*$F(1,73)=4.376$, $p=0.04$*) with respect to operator performance. In low task complexity, participants reported higher subjective performance (*$M=4.32$, $SD=1.00$*) using the high LOA mode compared to the low LOA mode (*$M=3.74$, $SD=1.28$*). At high task complexity, however, a reverse trend was observed – the low LOA mode showed higher reported performance results

(*$M=4.50$, $SD=0.76$*) compared to the high LOA mode (*$M=4.16$, $SD=1.21$*). The effect of LOA mode alone (*$F(1,73)=0.307$, $p=0.581$*) or task complexity alone (*$F(1,73)=1.878$, $p=0.175$*) did not have a significant effect on the reported performance.

Effort. The interaction between the LOA mode and task was not significant (*$F(1,73)=0.875$, $p=0.353$*), neither was LOA mode alone as a main effect (*$F(1,73)=0.008$, $p=0.927$*). As expected, in the high complexity task (*$M=2.41$, $SD=1.04$*), participants reported more exertion of effort (*$F(1,73)=14.047$, $p<0.01$*) than in the low complexity task (*$M=1.71$, $SD=0.90$*).

Frustration. The interaction effect of LOA mode and task complexity was significant (*$F(1,73)=6.701$, $p=0.012$*). In the low complexity task, participants reported higher frustration while using the low LOA mode (*$M=2.00$, $SD=1.16$*) compared to the high LOA mode (*$M=1.47$, $SD=0.70$*). The opposite was the case in the high complex task, where results revealed higher frustration in using the high LOA mode (*$M=2.32$, $SD=1.25$*) compared to when using the low LOA mode (*$M=1.75$, $SD=1.12$*).

The overall perceived workload rating for all workload dimensions confirmed that the difference in task complexity was significant (*$F(1,73)=17.51$, $p<0.01$*). The high complexity task placed a higher demand (*$M=49.23$, $SD=12.90$*) on the participants compared to the low complexity task (*$M=40.96$, $SD=10.31$*).

The correlation between participants' video gaming experience and the aggregated perceived workload scores, though slightly negative, was not found to be significant (*r=-0.091, n=77, p=0.431*).

4.3Situation Awareness

Complexity of Interaction. The interaction of the LOA mode and task complexity was not significant (*F(1,73) =2.378, p=0.127*).The LOA mode (*F(1,73)=0.741, p=0.392*) and task complexity (*F(1,73)=2.298, p=0.134*) also did not significantly influence the interaction complexity. However, participants perceived the interaction with the system to be more complex in the high complexity task when using the high LOA mode, which was not the case while using the low LOA mode.

Focus of Attention. LOA mode and task complexity had an interaction effect on participants' focus of attention (F(1,68)=4.649, p=0.035). While performing the low complexity task, participants concentrated their attention on more aspects of the interaction while using the low LOA mode (M=3.63, SD=1.74) compared to the condition where they used the high LOA mode (M=2.79, SD=1.93). This focus of attention was reversed in the high complex task, where participants concentrated on more aspects of the interaction in the high LOA (M=3.58, SD=1.92) mode than in the low LOA mode (M=3.15, SD=1.84).

Information Quantity. The perceived information quantity reported by the participants refers to the difference in information the participants gained about the environment for different LOAs at different task complexities. The interaction of LOA and task complexity did not have a significant effect on the perceived information quantity (*F(1,73)=0.179, p=0.674*). However, the pattern of information gained with respect to the LOA modes changed in the different task complexities, similar to the trend for focus of attention. In the low complexity task, participants reported that they gained more information about the environment when using the low LOA mode (*M=5.58, SD=1.07*) compared to the high LOA mode (*M=5.53, SD=1.12*). In the high complexity task, however, the reverse was the case – participants reported to have gained more information while using the high LOA (*M=5.42, SD=1.02*) relative to when using the low LOA mode (*M=5.25, SD=1.37*).

4.4System Usability

An interaction effect was observed between the LOA mode and task complexity with respect to the confidence in the system while using it (F(1,73)=5.067, p=0.027). In the low complexity task, participants reported higher confidence using the high LOA mode (M=4.53, SD=0.61) compared to the assisted teleoperated mode (M=4.00, SD=0.94), whereas in the high complexity task participants reported higher confidence using the assisted teleoperation mode (M=4.15, SD=0.81 vs. M=4.00, SD=1.00).

The aspect of the SUS questionnaire evaluating the integration of the system's various functions was also significant (F(1,73)=4.013, p=0.049) with respect to the LOA mode. Participants considered the system functions more integrated in the high LOA mode (M=4.24, SD=0.75) compared to the low LOA mode (M=3.92, SD=0.87). The influence of the LOA mode and task complexity was not significant in the other aspects of the SUS questionnaire. The LOA mode, however, significantly influenced the aggregated usability score for all the participants (F(1,73)=4.174, p=0.045). The usability scores were higher in the high LOA mode (M=59.00, SD=5.07) compared to the low LOA mode (M=56.87, SD=6.01). Although the mean scores were lower than the SUS-recommended 68% [5], 85% of the participants considered the system easy to use.

5 DISCUSSION

The presented study examines LOA implementation and use in the context of an MRP system operated through a user interface. The primary contribution was the development and evaluation of two LOA designs – assisted teleoperation (low LOA) mode and autonomous (high LOA) mode to support users in different task complexity situations. Some of the results should be taken with caution due to the relatively small number of participants; it is possible that more comprehensive user studies provide a more definitive picture on the relation between LOA and task complexity. In addition, we acknowledge that we did not evaluate dependency on user background factors, such as participants' age, gender and video gaming experience, which may have introduced bias into the results.

5.1Impact of LOA in MRP systems

The influence of the implemented LOA modes was observed only between the different task complexity levels. As the task complexity increased, the LOA which engaged participants more in managing the robot's functions yielded higher performance compared to the LOA with higher robot autonomy, in line with *H1*.

Previous studies [46] and Onnasch *et al.* [30], involving both expert and non-expert users revealed an overall improvement in performance with increasing automation for routine tasks. However, it was stated that in other situations involving tasks with more situational demands, critical decisions and action implementation, the performance declined with higher automation. This can be associated with those situations in our study in which the higher LOA (autonomous navigation mode) produced higher performance in the low complexity (and less demanding) task. In the high complexity task, which demanded more critical decisions and actions and in which more automation failures occurred, the lower LOA (assisted teleoperation mode) yielded higher performance.

A decline in workload was observed as the task complexity increased while using the high LOA mode (in line with *H2*). The reason for this might be connected with the frustration experienced by the participants in the higher task complexity when the automation failed or did not perform as expected (as seen in the frustration dimension of the NASA-TLX). In these situations, participants switched to a lower automation, perhaps to facilitate easier handling of some of these challenges as noted in [26] where a lower LOA was found to better facilitate easier interaction. The switching however incurs some switch costs [19, 49] which could have contributed to the frustration observed in the high LOA mode. This switch cost, may also have contributed to the reason why most of the participants did not switch when the task complexity was low.

Consistent with previous findings that lower LOA tends to improve the SA of users [14, 30], in the low complexity task, the assisted teleoperation mode appeared to provide better situation awareness in terms of focus of attention and the information participants gained about the environment (in line with *H3*). Moreover, participants seemed to miss fewer details about the environment, as seen in the objective measure assessing missed objects. This relation was reversed in the more complex task, which required a higher degree of awareness – a higher level of automation produced higher SA, as participants seemed to be better able to detect the obstacles. This concurs with the view of [19], arguing that the outcome of LOA implementations may vary with different task demands and advocating for the characterization of these LOA models in different tasks, contexts and situations in order to collate the prevalent trends for model improvements.

5.2Users' Attitudes Towards Automation

Most participants used the automated functions in the high LOA mode as they were guided to use it. Their confidence in the automation appeared to increase with use, as observed in section 4.4. However, along with this rise in confidence, one of the observed behaviors was overreliance on the automation without recognizing its limitations.

On the other hand, disuse of the automation was also observed, especially when the high LOA mode failed, delayed or did not perform as expected. Some of the participants who switched to the low LOA mode mentioned that the robot did not provide sufficient information in such situations to enable them to take prompt actions. This might be attributable to a sense of responsibility for system outcome, which can positively affect error detection tendencies by the human operator [18, 19].

Another observation was a form of satisficing behavior. Several participants did not exhaustively explore all control options, even though they could potentially yield better performance, e.g., the use of the map for high LOA or the trackball-like interface in the low LOA mode. Some participants simply continued using the conventional arrow control keys to navigate the robot since they were familiar with it and it gave them a 'good enough' outcome. This behavior of accepting a readily identifiable operational solution that meets some minimum level of performance can mediate the use of automation, as noted by Kaber *et al.* [18]. But it also has the tendency to lead to suboptimal solutions that could be detrimental to performance in general [19].

The usability assessment outcome was lower than the recommended 68% in SUS [5]. This may be due to the complexity of the user interface which the initial training did not completely overcome. The participants' comments reveal various areas of the design which could be amended to enhance the usability of the system. The comments are related to improved feedback from the interface, error handling, video quality of the robot's cameras and availability of zooming capabilities. Responses with regards to the ease of use and learnability of the LOA modes, however, revealed satisfactory outcomes. This highlights the potential for improved usability in complex tasks using the LOA options that are available (in line with H_4).

The users seemed to adapt the control options within the LOA modes successfully. This aligned with the goal of including the control options in the design to achieve seamless transitioning between control modes. Overall, participants' responses concerning the control options provided within each LOA mode revealed a relatively high degree of satisfaction.

6CONCLUSIONS AND FUTURE WORK

The user study yielded valuable insights into participants' preferences and which characteristics of the operator interface related to LOA should be modified to enhance the user experience and performance.

It is recommended that human operators be kept in the loop in all LOA modes. In the present context, this translates to using LOA modes that keep the users more involved in the task (such as the low LOA mode) to guard against overreliance while improving detection of potential failures or conflicts. In addition, the higher LOA mode can be improved in the future to minimize the need for switching and fine-tuning. In situations when it is desired or required, however, switching should be effortless and seamless, incurring as little penalty to users' mental workload and situation awareness as possible (following the results in section 4.4).

The users' attitudes towards the automation (section 5.2) can also inform some recommendations for further LOA development in MRP systems, which include clarity of feedback from the robot to ensure that users remain aware of its actions at all times and in all LOA modes. Options for error handling are further recommended to be

included in the LOA modes as part of the fallback mechanisms in cases when the robot fails (according to the comments in section 5.2).
This encourages users to detect and resolve errors, provided the tools for resolution are made available.

Ongoing work is focused on increased transparency of the high LOA mode and visual markers indicating close proximity to obstacles in the front and on the sides. We will further investigate effective measures to increase users' spatial awareness with respect to the robot's immediate surroundings, which will require tests with different types of cameras and interfaces along with their positioning on the platform. Moreover, future work should investigate additional interaction functions, e.g., zooming functions for the camera and extensive feedback from the robot. By making these adjustments, we expect the performance and usability with the direct teleoperation mode to improve and task completion time to decrease. In this way, we hope to provide a step forward in advancing MRP systems into markets and enabling them to become viable tools that add value to people's everyday lives.

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REFERENCES

[1] Jenay Beer, Arthur D Fisk, and Wendy A Rogers. 2014. Toward a framework for levels of robot autonomy in human-robot interaction. *Journal of Human-Robot Interaction* 3, 2 (2014), 74.
[2] Charles E Billings. 1991. Human-centered aircraft automation: A concept and guidelines. (1991).
[3] John R Boyd. 1996. The essence of winning and losing. *Unpublished lecture notes* 12, 23 (1996), 123–125.
[4] Per Øivind Braarud. 2001. Subjective task complexity and subjective workload: Criterion validity for complex team tasks. *International Journal of Cognitive Ergonomics* 5, 3 (2001), 261–273.
[5] John Brooke et al. 1996. SUS-A quick and dirty usability scale. Usability evaluation in industry 189, 194 (1996), 4–7.
[6] Brad Cain. 2007. A review of the mental workload literature. Technical Report. Defence Research And Development Toronto (Canada). [7] Donald J Campbell. 1988. Task complexity: A review and analysis. *Academy of management review* 13, 1 (1988), 40–52.
[8] Amedeo Cesta, Gabriella Cortellessa, Andrea Orlandini, and Lorenza Tiberio. 2012. Evaluating telepresence robots in the field. In International Conference on Agents and Artificial Intelligence. Springer, 433–448.

[9] S. Coradeschi, A. Cesta, G. Cortellessa, L. Coraci, J. Gonzalez, L. Karlsson, F. Furfari, A. Loutfi, A. Orlandini, F. Palumbo, F. Pecora, S. von Rump, A.
Stimec, J. Ullberg, and B. Otslund. 2013. GiraffPlus: Combining social interaction and long term monitoring for promoting independent living. In *2013 6th International Conference on Human System Interactions (HSI)*. IEEE, 578–585. https://doi.org/10.1109/HSI.2013.6577883

[10] Jacob W Crandall and Michael A Goodrich. 2002. Characterizing efficiency of human robot interaction: A case study of shared-control teleoperation. In *IEEE/RSJ international conference on intelligent robots and systems*, Vol. 2. IEEE, 1290–1295.

[11] Sidney WA Dekker and David D Woods. 2002. MABA-MABA or abracadabra? Progress on human–automation co-ordination. *Cognition, Technology & Work* 4, 4 (2002), 240–244.

[12] Mica R Endsley. 2001. Designing for situation awareness in complex systems. In *Proceedings of the Second International Workshop on symbiosis of humans, artifacts and environment*. 1–14.

[13] Mica R Endsley and David B Kaber. 1999. Level of automation effects on performance, situation awareness and workload in a dynamic control task. *Ergonomics* 42, 3 (1999), 462–492.

[14] Mica R Endsley and Esin O Kiris. 1995. The out-of-the-loop performance problem and level of control in automation. *Human factors* 37, 2 (1995), 381–394.

[15] Michael Greenstone and Vishan Nigam. 2020. Does social distancing matter? *University of Chicago, Becker Friedman Institute for Economics Working Paper* 2020-26 (2020).

[16] Sandra G Hart and Lowell E Staveland. 1988. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In *Advances in psychology*. Vol. 52. Elsevier, 139–183.

[17] Shanee S Honig, Tal Oron-Gilad, Hanan Zaichyk, Vardit Sarne-Fleischmann, Samuel Olatunji, and Yael Edan. 2018. Toward socially aware person-following robots. *IEEE Transactions on Cognitive and Developmental Systems* 10, 4 (2018), 936–954.

[18] David Kaber, Karl Kaufmann, Amy L Alexander, Sang-Hwan Kim, James T Naylor, Lawrence J Prinzel III, Carl Pankok Jr, and Guk-Ho Gil. 2013. Testing and validation of a psychophysically defined metric of display clutter. *Journal of Aerospace Information Systems* 10, 8 (2013), 359–368.

[19] David B Kaber. 2018. Issues in human–automation interaction modeling: Presumptive aspects of frameworks of types and levels of automation.
Journal of Cognitive Engineering and Decision Making 12, 1 (2018), 7–24.

[20] Andrey Kiselev, Annica Kristoffersson, and Amy Loutfi. 2014. Combining Semi-autonomous Navigation with Manned Behaviour in a Cooperative Driving System for Mobile Robotic Telepresence. In *European Conference on Computer Vision*. Springer, 17–28.

[21] Andrey Kiselev, Annica Kristoffersson, Francisco Melendez, Cipriano Galindo, Amy Loutfi, Javier Gonzalez-Jimenez, and Silvia Coradeschi. 2015. Evaluation of using semi-autonomy features in mobile robotic telepresence systems. In *2015 IEEE 7th International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM)*. IEEE, 147–152.

[22] Andrey Kiselev and Amy Loutfi. 2012. Using a mental workload index as a measure of usability of a user interface for social robotic telepresence. In
2nd Workshop of Social Robotic Telepresence in Conjunction with IEEE International Symposium on Robot and Human Interactive Communication 2012.

[23] Annica Kristoffersson, Silvia Coradeschi, and Amy Loutfi. 2013. A review of mobile robotic telepresence. *Advances in Human-Computer Interaction* 2013 (2013), 3.

[24] Francois Michaud, Patrick Boissy, Daniel Labonte, Helene Corriveau, Andrew Grant, Michel Lauria, Richard Cloutier, Marc-André Roux, Daniel Iannuzzi, and Marie-Pier Royer. 2007. Telepresence Robot for Home Care Assistance.. In *AAAI spring symposium: multidisciplinary collaboration for socially assistive robotics*. California, USA, 50–55.

[25] Neville Moray. 1986. Monitoring behavior and supervisory control. (1986).

[26] Samuel Olatunji, Noa Markfeld, Dana Gutman, Shai Givati, Vardit Sarne-Fleischmann, Tal Oron-Gilad, and Yael Edan. 2019. Improving the Interaction of Older Adults with a Socially Assistive Table Setting Robot. In *International Conference on Social Robotics*. Springer, 568–577.

[27] Samuel Olatunji, Tal Oron-Gilad, Noa Markfeld, Dana Gutman, Vardit Sarne-Fleischmann, and Yael Edan. 2020. Levels of Automation and Transparency: Interaction Design Considerations in Socially Assistive Robots for Older Adults. *IEEE Transactions on Human-Machine Systems* (2020).

[28] Samuel Olatunji, Tal Oron-Gilad, Vardit Sarne-Fleischmann, and Yael Edan. 2020. User-centered feedback design in person-following robots for older adults. *Paladyn, Journal of Behavioral Robotics* 11, 1 (2020), 86–103.

[29] Dan R Olsen and Michael A Goodrich. 2003. Metrics for evaluating human-robot interactions. In *Proceedings of PERMIS*, Vol. 2003. 4.

[30] Linda Onnasch, Christopher D Wickens, Huiyang Li, and Dietrich Manzey. 2014. Human performance consequences of stages and levels of automation: An integrated meta-analysis. *Human factors* 56, 3 (2014), 476–488.

[31] Andrea Orlandini, Annica Kristoffersson, Lena Almquist, Patrik Björkman, Amedeo Cesta, Gabriella Cortellessa, Cipriano Galindo, Javier GonzalezJimenez, Kalle Gustafsson, Andrey Kiselev, Amy Loutfi, Francisco Melendez, Malin Nilsson, Lasse Odens Hedman, Eleni Odontidou, Jose Raul Ruiz-Sarmiento, Mårten Scherlund, Lorenza Tiberio, Stephen von Rump, and Silvia Coradeschi. 2016. ExCITE project: A review of forty-two months of robotic telepresence technology evolution. , 204–221 pages. https://doi.org/10.1162/PRES{_}a{_}00262

[32] Amit Kumar Pandey and Rodolphe Gelin. 2018. A mass-produced sociable humanoid robot: Pepper: The first machine of its kind. *IEEE Robotics & Automation Magazine* 25, 3 (2018), 40–48.

[33] Raja Parasuraman, Thomas B Sheridan, and Christopher D Wickens. 2000. A model for types and levels of human interaction with automation. *IEEE Transactions on systems, man, and cybernetics-Part A: Systems and Humans* 30, 3 (2000), 286–297.

[34] Raja Parasuraman, Thomas B Sheridan, and Christopher D Wickens. 2008. Situation awareness, mental workload, and trust in automation: Viable, empirically supported cognitive engineering constructs. *Journal of cognitive engineering and decision making* 2, 2 (2008), 140–160.

[35] André Potenza and Alessandro Saffiotti. 2018. One Robot and Two Humans: Some Notes on Shared Autonomy in the Case of Robotic Telepresence.. In *IJCAI2018, Workshop on Autonomy in Teams, Stockholm, Sweden, 13 July, 2018*.

[36] Martin Rasmussen, Martin Inge Standal, and Karin Laumann. 2015. Task complexity as a performance shaping factor: A review and recommendations in Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) adaption. *Safety science* 76 (2015), 228–238.

[37] Donald Redfoot, Lynn Feinberg, and Ari N Houser. 2013. *The aging of the baby boom and the growing care gap: A look at future declines in the availability of family caregivers*. AARP Public Policy Institute Washington, DC.

[38] Worasak Rueangsirarak, Anthony S Atkins, Bernadette Sharp, Nopasit Chakpitak, and Komsak Meksamoot. 2012. Fall-risk screening system framework for physiotherapy care of elderly. *Expert Systems with Applications* 39, 10 (2012), 8859–8864. [39] J Sauro. 2012. 10 things to know about the Single Ease Question (SEQ). *Measuring U, 2012* (2012).

[40] Thomas B Sheridan and William L Verplank. 1978. *Human and computer control of undersea teleoperators*. Technical Report. Massachusetts Inst of Tech Cambridge Man-Machine Systems Lab.

[41] Kyriacos Shiarlis, Joao Messias, Maarten van Someren, Shimon Whiteson, Jaebok Kim, Jered Hendrik Vroon, Gwenn Englebienne, Khiet Phuong Truong, Noé Pérez-Higueras, Ignacio Pérez-Hurtado, et al. 2015. TERESA: a socially intelligent semi-autonomous telepresence system. In *Workshop on Machine Learning for Social Robotics 2015*.

[42] Aaron Steinfeld, Terrence Fong, David Kaber, Michael Lewis, Jean Scholtz, Alan Schultz, and Michael Goodrich. 2006. Common metrics for human-robot interaction. In *Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction*. 33–40.

[43] Richard M Taylor. 2017. Situational awareness rating technique (SART): The development of a tool for aircrew systems design. In *Situational awareness*. Routledge, 111–128.

[44] Marialena Vagia, Aksel A Transeth, and Sigurd A Fjerdingen. 2016. A literature review on the levels of automation during the years. What are the different taxonomies that have been proposed? *Applied ergonomics* 53 (2016), 190–202.

[45] Christopher D Wickens, Justin G Hollands, Simon Banbury, and Raja Parasuraman. 2015. *Engineering psychology and human performance*. Psychology Press.

[46] Christopher D Wickens, Huiyang Li, Amy Santamaria, Angelia Sebok, and Nadine B Sarter. 2010. Stages and levels of automation: An integrated meta-analysis. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 54. Sage Publications Sage CA: Los Angeles, CA, 389–393.

[47] Earl L Wiener. 1985. Cockpit automation: In need of a philosophy. *SAE Transactions* (1985), 952–958.

[48] Robert E Wood. 1986. Task complexity: Definition of the construct. *Organizational behavior and human decision processes* 37, 1 (1986), 60–82.

[49] Glenn Wylie and Alan Allport. 2000. Task switching and the measurement of “switch costs”. *Psychological research* 63, 3 (2000), 212–233.

[50] Oded Zafrani and Galit Nimrod. 2019. Towards a holistic approach to studying human–robot interaction in later life. *The Gerontologist* 59, 1 (2019), e26–e36.

Chapter 5: Interaction design using levels of automation and transparency

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Levels of Automation and Transparency: Interaction Design Considerations in Assistive Robots for Older Adults

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***Abstract*— It is important to spur older adults to remain active when interacting with assistive robots. This study proposed a schematic model for integrating levels of automation (LOA) and transparency (LoT) in assistive robots to match the preferences and expectations of older adults. Two distinctive test cases were developed to examine interaction design considerations for robots working with older adults in everyday tasks: a person-following task with a mobile robot and table setting task with a robot manipulator. Metrics to evaluate LOA and LoT design combinations are defined. Evaluations in user studies with older adults revealed that LOA and LoT combinations influenced interaction elements. Low LOA and high LoT encouraged older adults to engage in the activity while receiving adequate information regarding the robot's behavior. The combination of objective and subjective metrics is important to provide a holistic framework for evaluating the interaction.**

***Index Terms*—Human-robot interaction, level of automation, level of transparency, assistive robots, older adults, interaction design, socially assistive robots.**

I. Background

THE global population of older adults (aged 65+) is increasing rapidly without a commensurate growth in the population that can support them [1]. This is creating an eldercare gap where the scarcity of caregivers, social support and healthcare professionals have left many older adults with several barriers to aging in place [2]. Assistive robots (AR) can help reduce these barriers, facilitating independence and promoting successful aging (e.g., [3]–[5]). While there has been progress in AR design and development in many daily applications [6], several challenges remain [7]. One major challenge is the lack of fit between user expectations of the robot's role and the robot's capabilities and behavior [8]. This may cause an interaction gap which can, on one hand, lead to over-expectations, where older adults over-rely on the robot, presuming it can do what it is not designed for, misuse or abuse [9]. On the other hand, under-expectations where older adults ignore robots' capabilities leading to disuse or abandonment.

A reliable design should meet the needs and preferences of older adults while keeping them informed of the robot's actions, capabilities and limitations [9]. This calls for an interaction design which pulls together several interaction-related elements to ensure older adults' preferences, expectations and characteristics match with a robot's behavior and the tasks it can perform [10]. This paper focuses on the integration of level of automation (LOA) with level of transparency (LoT) of ARs for older adults to keep them active along the interaction.

II. Related Work

We begin with definitions of LOA and LoT. The levels at which a human operator controls an automatic process are classified as LOAs [11]. LOA defines the degree of robot involvement, the degree to which automation is employed in a given task and the level of assistance given to the user [12]. In the lowest LOA, the user manually controls the operations of the robot. In the highest LOA, the robot is fully autonomous. Intermediate LOAs can be viewed from the perspective of user consent versus exception. In the robot-oriented semi-autonomous level (Management by Exception - MBE) the robot informs the user as it initiates and implements actions unless the user objects. In the human-oriented semi-autonomous level (Management by Consent – MBC) the user must explicitly agree to suggested actions before they are carried out by the robot. MBC presumably increases users' awareness of, and control over the robot's behavior, but it does so at the cost of increased communication demands. Previous research in an aviation application [13] looked at MBC breakdowns as a function of conflict detection and found that operators were very poor at detecting conflicts before the system issued the request for consent. Hence, effective MBC must be supported by the system's interfaces (i.e., be connected with the systems' LoT). Furthermore, even highly trained operators have difficulties in detecting conflicts - raising concerns for ARs used by older adults. Difficulties are evident in MBE systems as well, since the human may not promptly detect potential conflicts, affecting failure avoidance and failure recovery times [14]. Therefore, interaction design is critical in both MBC and MBE since users cannot consent or object to something that they cannot see, detect, or understand. Designing LOAs to fit needs and demands of older-adult users is therefore substantial for interaction design in AR operations [15]. It is both essential and challenging to keep the older adult involved in the task while controlling the robot.

LOA design can be modelled by the four stages of information processing [16] denoted as the OODA loop [17]: acquiring information (Observe), processing information (Orient), making decisions (Decide) and taking action (Act).

Acquiring Information includes elements such as the illumination of the environment, and clutter in the environment. It may also include elements such as items to be set on a dining table or position where the items should be. *Processing Information* requires generating options for performing the task. It involves options such as movement speed and distance to keep to a person when following. It may involve the type of items to set for a person and the order of setting. *Making Decisions* entails identifying which of the options to select in performing the task. This may involve deciding on the most appropriate following angle and distance of the robot when following a person in a person following (PF) setting or deciding upon the order of setting items on a dining table for a table setting (TS) task. *Taking-Action* are steps associated with the decision made. Examples include following the user as she/he moves along a corridor (PF) or picking up a plate and placing it on the table in front of the user (TS).

Level of transparency (LoT) is the degree of information (information quantity) provided to the user related to the state, reasoning process and future plans of the system [18]. Specifying the amount and relevance of information presented by the robot to the user to maintain the interaction [19], [20]. The information presented by the robot must conform with perceptual and cognitive peculiarities of the older adults [10], [21], [22] and relate to the environment, task, and robot [20]. Too little information may not be sufficient to ensure reliable interaction with the robot [8], whereas too much may cause confusion and error [20].

LoT design can be modelled using the Situation Awareness based Transparency model (SAT) with the following levels [18]: *Purpose and perception* - the LoT which provides information on the current state of environment, task, robot, human or interaction. *Comprehension and reasoning* - the LoT that defines how the state of the environment, task, robot, human or interaction may affect the users' interaction with the robot. *Projection and prediction* - the LoT that gives information on the next state in the interaction based on the present status and other intervening factors.

To ensure effective interaction, we propose a model for how to integrate LOA and LoT design (Section III). This integration is then evaluated in user studies in two distinctive robotic test cases (Sections IV and V): 1) Person following (PF) with a mobile robot used to follow an older adult from behind and carry personal items; and 2) Table setting (TS) of a dining table for a meal with a robot manipulator. Each evaluation included a 2x2 design of two LOAs and two LoTs. The TS data was obtained from previous work [23], in which we evaluated the feasibility of incorporating LOA-LoT combinations for a robot arm in a domestic setting [23]. The LOA-LoT schematic model was not described in previous work [23] where only preliminary analyses were included. In the current work, we additionally propose metrics to evaluate LOA-LoT. The aim is to determine whether there are commonalities in LOA-LoT interaction design implementations that go beyond specific ARs or tasks. These commonalities, if exist, can lead to design recommendations for LOA-LoT combinations to improve older adults' interaction with ARs. Section III describes in detail the LOA-LoT schematic design model, the metrics for evaluation and the research hypotheses. Section IV describes the experimental details for the PF and TS test cases. Results for LOA-LoT combinations are presented in section V. Discussion, design guidelines, implications, limitations of the research and future work are given in section VI.

III. Schematic Model for Integrating LOA-LOT

A schematic model is proposed (Fig. 1) for integrating LOA and LoT settings in a user interface through which robot involvement (LOA) and information quantity (LoT) can be adjusted for the task.

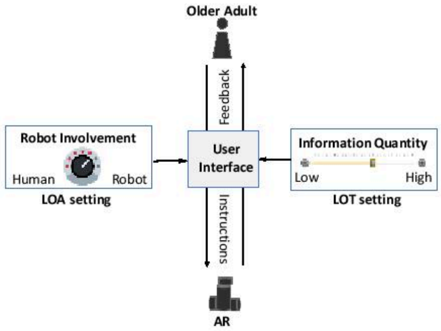

Fig. 1. A schematic model for Integrating LOA and LoT with interaction design for older adults and ARs.

The model must be adapted for each test case using a designated interface, taking into account ecological interface design principles [24]. LOA delineates the robot's role and actions expected in the interaction including information exchange between the robot and the user in the form of instructions and feedbacks. LoT explores what the content of this information from the robot should be. Significant interaction between LOA and LoT is expected, as lower levels of automation require more involvement of the user and more information [13]. The mode through which the information exchange occurs is considered in the user interface design to ensure it is convenient for the users to receive the information while performing the task.

A. Design of the LOA Modes

A major consideration in designing the LOA mode was to keep the older adult involved in the task while controlling the robot. Four levels of automation were carefully weighed based on human-automation systems design guidelines and recommendations [25]: *Robot alone:* the robot performs all actions without any form of human involvement. *Robot Oriented Semi Autonomy (MBE):* the robot implements actions unless the user objects and informs the user of the implemented action following its execution. *Human Oriented Semi Autonomy (MBC):* the user must explicitly agree to suggested actions before they are performed by the robot. *Human alone:* the robot is not involved in any part of the task. The human performs all actions.

To encompass the four levels at different phases of the

OODA loop, two LOA modes were designed to ensure: a) that the human is always kept in the loop, regardless of the automation level, and b) that the robot helps the human at all times, but as least as possible, so human skills are maintained and sedentary behavior is avoided. The specific LOA combinations within the OODA loop components define the following two tested LOA modes (see also Fig. 2).

Low LOA mode: the robot minimally assists the human in acquiring information related to the task by presenting information through the applicable interface. The robot also assists in the information processing by providing options through which the task could be performed. The human must agree to the suggestions before the operation can continue. The human then solely makes the decision regarding what should be done while the robot assists in the execution of the actions.

High LOA mode: the robot is more involved than the human in acquiring information regarding details of the task. This information is fully processed by the robot. All decisions related to the task are taken only by the robot. The robot executes the decision but can be interrupted by the human.

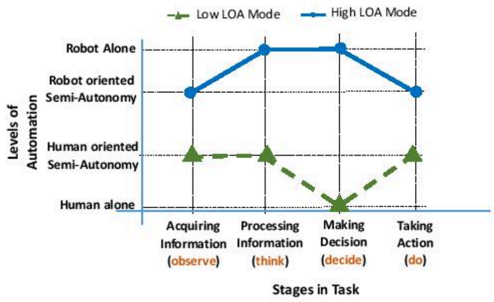

Fig. 2. LOA modes designed for older adults' interaction with ARs. The tested LOA modes are described as an OODA loop [27]. In the High LOA mode, decisions are taken by the AR and the human can overrule upon execution. In the Low LOA mode, the human makes the decision alone.

B. Design of the LoT Modes

The aim of the LoT design was to provide as much information as needed to the user at every point in time without overloading the user. During the interaction, the following information classes are provided to the user:

Task-related information: information from robot to the user regarding its state, or its actions as connected with the task at hand. It includes details of the task such as time required to complete the task, constraints connected to the task, demands and dependencies in the task, requirements for the task, progress in the task [18], [26], [27].

Environment-related information: the type of environment (e.g. indoors, outdoors, corridor, open space), conditions prevalent in the environment (e.g., illumination conditions, clutter, obstacles, weather conditions), environmental constraints, and safety-related environmental information [3], [20], [28], [29].

Robot-related information: information pertaining to the operation and behavior of the robot i.e., the degree of reliability of the robot, principles underlying its decision making and all other (e.g. information on how to use a specific feature on the robot or on battery charge level of the robot) [30], [31]).

Human-related information: the human's physical condition (e.g., heartrate, tiredness), cognitive state (e.g., engrossed, confused), emotional state or mood (e.g., happiness, fear). It also includes information regarding the workload or stress the human is experiencing [32].

Interaction-related information: details of the human and robot's roles in the interaction, shared awareness and dynamics of the teamwork [32]. It entails information of how subtasks are allocated as the roles in the LOA condition being used and how each role would be executed.

Previous research on users' LoT preferences regarding the four classes of information (task, environment, robot, human,) [33] revealed that older adults preferred the *purpose and perception* transparency level for these different classes. Most older adults wanted the robot to be current and immediate, providing only status information. In some situations, they asked for a higher level of transparency to know why the robot took certain actions (*comprehension and reasoning*). In fewer cases, out of curiosity, they asked to know what the robot planned to do next (*projection and prediction*). Based on [31], the amount of information for each class of information was designed into the LoT modes set as follows (see also Fig. 3).

Low LoT mode: the robot presents status information regarding environment, task, robot and user. It also presents additional information to support the interaction in certain cases (e.g. if something is not functioning as expected).

High LoT mode: the robot presents status information regarding environment, projects the next stage in the task, gives reason for its actions, presents how information about the user could affect actions, and the future state of the interaction.

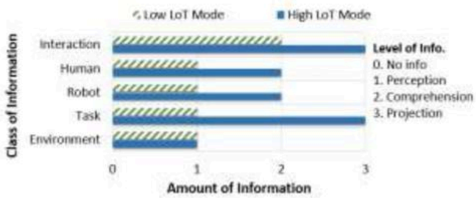

Fig. 3. The LoT conditions developed for the experimental test cases are described in terms of the class and amount of information the AR provides. In the High LoT the AR provides more predictions about all classes of information. In the Low LoT basic status information is given.

C. Interaction Design Metrics

Five metrics were defined to evaluate the LOA-LoT model: engagement, fluency, comfortability, understanding and trust. Each metric was composed of normalized objective and subjective metrics which were combined by an averaging function.

Normalization was conducted for each of the objective and subjective values using feature scaling to bring all values between 0 and 1, using the minimum and maximum values within each variable (1):

$$V_n = a + \frac{(v - v_{min})(b - a)}{v_{max} - v_{min}} \quad (1)$$

where V_n= normalized value between [a, b], with v_{max}= maximum value and v_{min}= minimum value.

The average values of all metrics were then combined to create one combined metric for each assessment metric (2):

$$METRIC = \frac{1}{n}\sum_{i=1}^{n}(Obj_i + Sub_i) \quad (2)$$

where $METRIC$= engagement, fluency, understanding, comfortability, trust as defined below
Obj = objective metrics; Sub = subjective metrics; n= total number of individual metrics combined for the trials.

An aggregated metric was then implemented to combine all metrics (3):

$$M_A = \frac{1}{5}\sum_{i=1}^{5}(E_i + F_i + U_i + C_i + T_i) \quad (3)$$

where M_A= aggregated metric, *E = engagement, F = fluency, U=understanding, C=comfortability, T=trust*

1) Engagement captures the details involved in initiating a connection between the human and the robot, maintaining that connection and regulating it till the end of the interaction [34]. Objective metrics include gaze duration of the users as they focused on the robot or GUI of the robot and the number of user-initiated voice and gesture responses in the interaction. Subjective metrics are assessed through questionnaires related to the attention given to the robot or GUI (using adaptations from the *Engagement perception for social robots*, attention dimension in [35]).
2) Fluency is the coordination of the shared task between the human and the robot for successful synchronization of plans and actions [26]. It can be measured objectively through task duration of concurrent activity, human and robot idle time, functional delay in the interaction. Subjective metrics are assessed through questionnaires on the timing of the robot's actions and feedbacks during the interaction (a subset of *Human-Robot Fluency Scale* in [36]).
3) Understanding is the accurate comprehension of details of the interaction to promote a successful interaction of the human with the robot [37]. It can be measured objectively through the number of clarifications made by the participant to the experimenter regarding the information the robot is providing. Another objective metric is the participants' reaction time while interacting with the robot. Subjective metrics are assessed through questionnaires on the comprehension of the robot's actions and information it provides during the interaction (understanding dimension of the *Situation Awareness Rating Technique* in [38])
4) Comfortability is the extent to which the human experiences ease, absence of stress, pain or other forms of discomfort resulting from interaction with the robot [39]. It can be measured objectively through physiological signals connected with stress, fatigue or relaxation such as heart rate difference measurement. Eye movements [39] observed in gaze shifting to monitor the robot's actions during the interaction can also indicate some degree of discomfort or lack of ease. Subjective metrics are assessed through questionnaires that relate to the ease of interaction with the robot, and extent of stress experienced during the interaction (a subset of the *Robotic Social Attributes Scale* [40])
5) Trust is the disposition to rely upon the abilities or capabilities of the robot based on a certain degree of satisfaction in level of performance [41]. It can be measured objectively in terms of proximity to the robot and in other actions reflecting degrees of dependence on the robot. Subjective metrics are assessed by questionnaires that relate to the extent of dependence on the robot and perceptions of mistakes the robot makes (a subset of the *Human-Robot Trust Scale* in [42])

IV. METHODS

Two experimental test cases representing robotic applications for daily living activities were developed: person-following (PF) and table setting (TS). Settings varied in terms of task demands, environmental constraints, robot type and capabilities, and user expectations.

A. Experimental platforms

1) Person-following mobile robot

A Pioneer LX mobile robot (50 cm width, 70 cm length and 45 cm height) was used (Fig. 4-left). It had an integrated on-board computer running on a 1.8 GHz Dual Core processor, and 2GB DDR3 RAM and laser rangefinder (SICK S300), positioned approximately 20 cm above the ground, to detect nearby obstacles and avoid them. The robot was programmed to stop if it detects an object 50 cm from its core. The Kinect camera was not specifically used in this study for navigation but was kept on the robot to provide semblance of a head for the robot. The robot followed the first person it detected by moving to a defined position behind the person (as set in the program). The person tracking and following commands were executed in ROS [43], [44] using OpenPTrack and sent to the onboard computer using a TPLINK router with wireless speed up to 300 Mbps. The angular and linear velocity of the robot was dynamically updated according to the angular displacement of the target and distance of target to the robot, respectively. Parameters such as maximum following speed (1.0m/s), acceleration coefficient (0.5), following distance (0.3m) and following angle (30˚) were set according to previous research recommendations for social following robots to ensure users' satisfaction, trust, comfort and overall perception of safety [45]–[47].

2) Table setting robot arm manipulator

A KUKA LBR iiwa 14 R820 manipulator was equipped with a pneumatic gripper and suction for picking and placing items at specific positions on the table. ROS was used to implement the task and link all modules which were programmed in Python [43]. A dedicated graphical user interface (GUI) was designed on a computer monitor placed near, to the left of the user to enable the user to give instructions to the robot and receive feedback from it.

B. Test cases task descriptions

1) Person-following task

The task required the participant to walk a designated path to retrieve an item placed at about 25m away from the participant with a mobile AR following him/her autonomously from behind. The study took place in a 2.5m wide corridor in a university laboratory building. The participant was expected to place the item on the robot after retrieving it and return to the start position for each one of the experimental conditions (Fig.4 – right). The robot continuously communicated with the participant regarding its state to keep the users aware of its actions [48] based on the feedback recommendations in previous studies [33] .

2) Table-setting task

In the table setting task [23] a robotic arm placed on a table in front of the user set a plate, a fork, a knife and a cup at specific positions on the table for the older adult in preparation for a meal (Fig. 5). Depending on the LOA, the older adult was involved in the process by deciding which item to set and in which order.

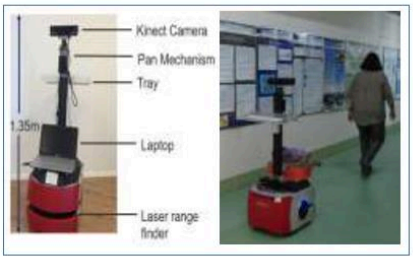

Fig. 4. Left, the Person-following (PF) robot platform. Right, the experimental setup with the robot following the user along a corridor.

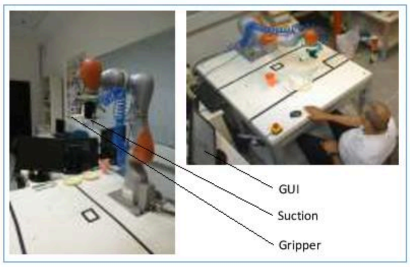

Fig. 5. Left, Table setting (TS) robot platform and experimental setup. Right, a participant instructing the robot, note the screen to the left of the user.

C. Experimental Design

Each experiment was designed as a mixed between- and within-participant design with LOA (High/Low) and LoT (High/Low) conditions manipulated in a similar manner for both test cases (Fig. 2-Fig. 3). Each participant experienced one test case. LOA was the between-participant variable. Participants completed the task twice in the LOA assigned to them, once for each LoT. LoT order was counterbalanced to avoid order effects.

The dependent variables were the aforementioned interaction design metrics adapted for each test case as detailed below and summarized in Table I.

Engagement: for PF, the extent to which a participant-initiated communication with the robot while gazing at the robot, and the duration of gazes that participants made toward the robot during this communication. For TS, the number of times participants looked towards the GUI where the robot's information was provided, gaze duration as participants focused on the robot, and the number of user-initiated voice and gesture responses unrelated to the task.

Fluency: for PF, robot idle time was not used due since the robot was actively and continuously following and tracking the participant.

Understanding: for PF, reaction time was measured by the time it took participants to react when the robot gave instructions such as 'I will follow you, as you move. You can start moving now'. In the TS, reaction time was not an indicative metric since participants sat right in front of the robot and the user interface afforded them the opportunity to promptly respond to the instructions the robot gave through the GUI (results [23] revealed immediate response).

Comfortability: for PF, this was measured as the number of times participants glanced back at the robot, where a glance back may indicate upon the discomfort of losing the robot. This was not indicative for the TS since participants were sitting in front of the robot. Each participant's heart rate at the beginning of the experiment was normalized to 100bpm. The difference in heart rate throughout the experiment and in each of the conditions was then calculated relative to this normalized value. An identical scale for the heart rate difference measurement was used in both test cases.

Trust: for PF was measured as the walking duration to pick an item without looking back at the robot following them from behind, and the time spent waiting for the robot when the robot lost track or was delayed. In the TS, it was measured in terms of the participants' perception of safety (categorized into 3 levels according to the initial location of the participant – (1) standing next to the robot, (2) sitting with hands on table, and (3) sitting far from the robot.

D. Hypotheses

The experimental evaluation aimed to assess LOA-LoT design combinations with the following hypotheses:

H1: There will be an LOA-LoT interaction effect on the overall performance and interaction quality as measured through the aggregated metric consisting of engagement, fluency, understanding, comfortability, and trust.

H2: Low LOA and high LoT will increase engagement.

H3: High LOA and low LoT will increase fluency.

H4: Low LOA and high LoT will increase understanding.

H5: Low LOA and high LoT will increase comfortability.

H6: Low LOA and high LoT will increase trust.

E. Participants

Twenty-four older-adult healthy participants with no major physical disability or impairment (14 females, 10 males) aged 62-85 (*M=75.4, SD=5.8*) were recruited via social networks and colleagues. Most of the participants were healthy. Only two of them had a slight physical challenge with walking. Most of the participants lived most of their adult years in Israel. Ten participated in the PF experiment and the other fourteen participated in the TS experiment. A preliminary discussion was held with each participant before the experiment to ascertain comfortability with the robot and ensure understanding of the procedure and fitness for the task.

TABLE I
INTERACTION DESIGN METRICS

Metrics	Objective Metrics	Subjective Metrics
Aggregated metric	Combination of all normalized metrics (2) into a single variable using the average function (1)	
Engagement	GUI gaze duration (seconds)* Robot gaze duration (seconds) User-initiated responses (counted) Human active time (seconds)*	My attention was focused on the robot while it was performing the task. My attention was focused on the GUI while performing the task *
Fluency	Robot idle time (seconds)* Functional delay of robot (seconds) Task completion time (seconds)	I felt that the information which was provided by the robot was in the right timing. I felt the actions of the robot were in the right timing
Understanding	Number of interruptions to ask for more clarification (counted from recorded videos of the interaction) Reaction time of the participants (seconds)†	I understood the robot well. I understood the information the robot presented to me.
Comfortability	Number of times participants were glancing back at the robot (counted from recorded videos of the interaction) † Heartrate difference (bpm)	I felt comfortable with the way the robot communicated with me. The experience with the robot made me stressed (R).
Trust	Overall time spent on the task of walking to pick item without looking back at the robot coming behind (seconds) † Perception of safety (location of participant with respect to the robot) *	During the experiment, I felt I could trust the robot. Did the robot make mistakes during the interaction? (R)

†PF – Metric for the Person Following experiment only *TS – Metric for the Table Setting experiment only R – reversed items

F. Experimental Procedure

Participants completed a preliminary questionnaire (consisting of demographic information, the Technology Adoption Propensity (TAP) [49] and the Negative Attitude towards Robots Scale (NARS) [50]) before being introduced to the robot and performing the task.

The PF experiment took place as described above. In the low LOA, the robot received the consent of the participant before it began to follow, but in the high LOA, it began following immediately. For the low LoT, the robot gave the participant status update regarding what it was doing (e.g., 'following', 'stopping') at a pace of 5 seconds. In the high LoT the robot provided its current actions and additional information on the reason for taking these action (e.g., 'stopping because there is an obstacle ahead').

In the TS experiment, the user initiated the robot's operation with a start button which served also as a 'stop at any time' button. In the high LOA, the robot set the items autonomously. In the low LOA, the robot acquired the participant's choice of items to set (via the GUI) in addition to consent for starting or stopping the operation. Information from the robot was presented in visual form through the GUI. The low LoT included text messages that specified the current action of the robot (e.g., 'bringing a plate', 'putting a fork'), the high LoT included in addition to this text the reason for the robot's actions, (e.g., 'I'm bringing the plate as you asked me').

Participants were told that the robot would behave differently in the two trials. After each trial, participants were given a post-trial questionnaire which used 3-point Likert scale with 3 representing "Agree" and 1 representing "Disagree". The 3-point scale was selected due to the challenge the older adults experienced in previous trials with the 5- and 7-point scales [51]. A final questionnaire was provided at the end of the experiment to enable the participants to explicitly retell their experience with the robot. All procedures were approved by the university's ethical committee.

G. Statistical Analyses

Analyses were performed using a two-tailed General Linear Mixed Model (GLMM) analysis. The fixed effects were the LOA and LoT and one random effect which accounted for individual differences among participants. To ensure that analyzed variables conform with the GLMM requirements, the variables that included time (e.g., gaze duration, human active time) were log transformed. The cumulative logit model was used for variables with ordinal values (e.g., perception of safety, questionnaire responses). The Wald chi-square test was included as a multi-variable generalization test to evaluate the multiple parameters involved in the analyses.

V. EXPERIMENTAL RESULTS

A. Characteristics of Users

Most of the participants were acquainted with the use of innovative technologies (*M=3.39, SD=0.72*). The TAP index [20] revealed that most participants were affirmative that technology could provide more control and flexibility in life (PF: *M=2.48, SD=1.59;* TS: *M=3.86, SD=1.17*). Participants showed confidence in learning new technologies (*M=2.95, SD=1.18*), were comfortable communicating with robots (*M=3.43, SD=1.50*) and trusted technology (*M=3.04, SD=1.58*). Eighty percent of the participants were positive about interacting with a robot (*M=4.14, SD=0.86*).

B. Aggregated metric

The means distribution of the combined objective and subjective data across the four LOA-LoT combinations for each of the evaluation metrics is presented in Fig. 6. The GLMM analyses revealed that there was a significant influence of LOA and LoT on the overall aggregated metric for PF (*F(3, 16)=3.91, p=0.026*) and TS (*F(3, 22)=2.35, p=0.033*). This confirms *H1*. Details of the significance for the aggregated metric and of the individual metrics are shown in Table II.

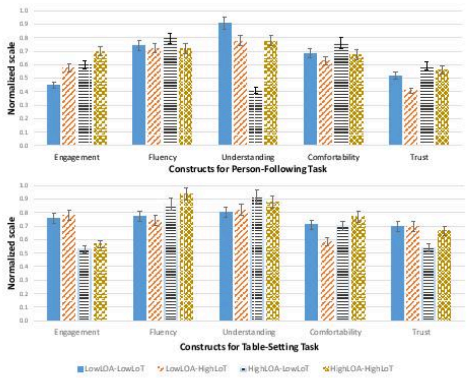

Fig. 6. Summary of normalized metrics for the two robotic test cases.

TABLE II
AGGREGATED METRIC IN BOTH TASKS (SIGNIFICANT HIGHLIGHTED)

		Person Following			Table Setting		
Metr		Obj	Sub	Cmb	Obj	Sub	Cmb
Eng	LOA	.33	.09	.03	.01*	.46	.01*
	LoT	.36	.18	.07	.65	.88	.42
	LOA*LoT	.68	.04	.03	.01*	.85	.01*
Flu	LOA	.34	.14	.73	.01*	.34	.01*
	LoT	.67	.62	.51	.92	.34	.57
	LOA*LoT	.67	.49	.89	.01*	.18	.01*
Und	LOA	.03	.24	.01*	.28	.77	.13
	LoT	.45	.24	.13	.93	.55	.84
	LOA*LoT	.01*	.07	.01*	.71	.93	.47
Com	LOA	.83	.28	.35	.09	.29	.06
	LoT	.48	.41	.28	.99	.45	.55
	LOA*LoT	.8	.59	.57	.2	.35	.03
Tru	LOA	.81	.18	.14	.29	.37	.17
	LoT	.80	.27	.36	.38	.61	.37
	LOA*LoT	.57	.44	.29	.60	.47	.26

Metr= Metrics, Eng=Engagement, Flu=Fluency, Und=Understanding, Com=Comfortability, Tru=Trust, Obj=Objective, Sub=Subjective, Cmb=Combination of objective and subjective *=p<0.01

C. Engagement

The LOA-LoT interaction had significant influence on engagement for both the PF task (*M=.58, SD=.16*), $X^2(3, N=20)=8.82$ $p=.03$) and the TS task (*M=.75, SD=.78*), $X^2(1, N=28)=30.91$, $p<.01$). The low LOA and high LoT significantly engaged the participants compared to the other experimental conditions (p<.01) in both test cases. This confirms *H2*.

D. Fluency

Fluency was not significantly affected by the LOA-LoT interaction in the PF task (*M=.74, SD=.16*), $X^2(3, N=20)=.652$ $p=.89$) but was significant in the TS (*M=.83, SD=.13*), $X^2(1, N=28)=13.05$, $p<.01$). The high LOA and low LoT significantly increased fluency compared to the other LOA-LoT combinations (p<.01) in the TS. This supports *H3* for the TS task only.

E. Understanding

Understanding was significantly affected by the LOA-LoT interaction in the PF task (*M=.72, SD=.25*), $X^2(3, N=20)=33.15$ $p<0.01$) but was not significantly affected in the TS (*M=.85, SD=.15*), $X^2(1, N=28)=2.51$, $p=.47$). Low LOA and high LoT conditions significantly increased understanding compared to other conditions (p<.01) in the PF. This supports *H4* for the PF task only.

F. Comfortability

Comfortability was not significantly affected by the LOA-LoT interaction in the PF (*M=.69, SD=.15*), $X^2(3, N=20)=2.03$ $p=.57$) but was significantly affected in the TS (*M=.69, SD=.14*), $X^2(1, N=28)=9.07$, $p=.03$). The high LOA and high LoT produced significantly higher level of comfort compared to the other conditions (p<0.1) in the TS. This supports *H5* for the TS task only.

G. Trust

The interaction effect of LOA-LoT on trust was not statistically significant in both test cases (PF: (*M=.52, SD=.19*), $X^2(3, N=20)=3.79$, $p=.29$); TS: (*M=.65, SD=.18*), $X^2(1, N=28)=4.06$, $p=.26$). *H6* is not supported.

VI. DISCUSSION

LOA-LoT interaction effects were found in both test cases for the aggregated metric and for engagement. Combining the low LOA (which promotes higher engagement) with high LoT (which provides more information) was observed to improve the interaction as assessed through the defined metrics. Summary of main findings is presented in Table III. Previous research had indicated that in high LOA, users can become frustrated due to a lack of control they sometimes feel [52]. More frustration can ensue if the users are not aware of what is happening [19]. Therefore, providing a higher degree of control (through the low LOA) and higher transparency (through the high LoT) can minimize these potential challenges when the older adults interact with their ARs. This also corresponds with previous recommendations for enhanced interaction design in aiming to improve the sense of control in the automation [52] and transparency in the robot's actions [19], [53].

A. Task dependent influences

The results for fluency, understanding and comfortability were not consistent implying that task-related factors influence the interaction.

For fluency, as an example, the LOA-LoT interaction was significant in the TS but not in the PF. This may be related to participants' workload; the PF task required participants to move forward, as the robot follows them from behind. Therefore, it is possible that they identified fewer delays in the interaction compared to the TS task where the participant sat at the table and passively observed the robot's actions. This probably led to the higher tendency of participants to notice delays in the process of setting the table. This is also related to the observations in [54] where participants indicated via the

TABLE III
SUMMARY OF MAIN FINDINGS

Finding	Confirmed Hypotheses	Supporting data
LOA-LoT interaction effects were found in both test cases for the aggregated metric consisting of engagement, fluency, understanding, comfortability and trust.	H1	Section V, B. Aggregated metric
Low LOA and high LoT increases engagement in both test cases	H2	Section V, C. Engagement

questionnaires delays they noticed. However, in both test cases the high LOA combinations increased the fluency.

The differences observed in understanding can also be explained by the different conditions prevalent in the test cases. Perhaps the difference in feedback modality through which the participants received information in the test cases affected their understanding, resulting in different needs for clarifications. Voice feedback coming from the robot behind the user (as was the case in the PF) may have afforded a different level of clarity than the visual feedback coming from the robot in front of the user (as is the case in the TS). Thus, the position of the user relative to the robot could also have influenced these differences.

These task dependent factors which influenced fluency and understanding may also have affected the comfortability. We cannot however assert these claims since the study did not specifically examine these interaction effect of these factors.

B. *Perception of the older adults toward the LOA-LoT design*

The older adults were confident to interact with the robots in both test cases. This could be seen in the willingness to participate in the experiment after the explanations had been made to them. They seemed to have a relatively high level of confidence interacting with the robot in all the conditions. This could explain the lack of significant difference in the experimental conditions for the trust metric in both test cases.

The older adults also preferred to be more involved and active in both test cases while they collaborated with the robot. Their responses in the questionnaires and discussions indicated that they considered the low LOA as an invitation by the robot to collaborate on tasks as opposed to the high LOA where they seemed to perceive the AR as more independent. They were also more particular about the LoT they preferred in each LOA mode. They considered the AR more communicative at the high LoT compared to the low LoT. Combining both low LOA and high LOT as a behavior of the AR appealed more to them on the interactive level. The behavior, as they described it, seemed to portray the AR more as a companion supporting them rather than a tool carrying out house chores in isolation.

These results are in line with our previous studies in which we investigated designs related to the LOA and LoT designs for similar tasks with young adults as participants [47], [54]. However, it seemed that younger adults preferred the higher LOA mode irrespective of the LoT mode. Further research should investigate into this.

VII. CONCLUSIONS

A. *Practical implications*

The study revealed the importance of integrating LOA with LoT in the design of ARs supporting older adults. The LOA-LoT integration proposed was successfully implemented and tested in the two test cases providing evidence for the feasibility and viability of the design in ARs. The satisfactory interaction of the older adult with the ARs in both test cases using the implemented model meets the expectations regarding the potential benefits of shared control and information sharing. This contributes to active physical and cognitive involvement which are important to encourage successful aging for older adults [55].

The significant results observed through the metrics proposed for evaluation of the LOA-LoT design also revealed the potential of using the defined metrics for further assessment of other HRI-related studies. The combination of objective and subjective metrics provides a holistic framework for evaluating the interaction and can be employed as a standard in HRI evaluation.

B. *Guidelines for LOA-LoT Design for Older Adults*

Guidelines for LOA-LoT designs in ARs for older adults' settings are proposed as follows:

- We recommend operating the robot at a low LOA to keep the older adult more actively involved in the task.
- Combining low LOA with high LoT helps to maintain older adults' awareness of the robot's operations without overloading them with information.
- LoT should be adapted to be suitable for the specific LOA, to ensure that the robot's actions match the expectation of the older adults.

C. *Limitations of the study*

The recommendations are based on two robotic test-cases with two different types of robots; preferences and the recommendations made might vary for other test cases. It is also worth noting that the older adults who participated in the user studies were mostly in the younger-old (65 to 74 years) and old-old (75 to 84 years) grouping. Only some of the participants were in the group of oldest-old (85 years and above). Also, all the participants were mostly healthy older adults who were physically and cognitively fit to come independently to the labs for experiments. Specific health status records, physical or mental needs were not collected from individual participants.

D. *Future research directions*

Future work should assess the robustness of the LOA-LoT design for different cases of task complexity, environmental changes, workload, malfunctions and user characteristics. The metrics defined in this study should be evaluated while assessing the LOA-LoT design for these cases. Other adaptable LOA-LoT options could also be explored to improve the interaction

Further investigations with older adults should include the oldest-old group and groups with varying physical or mental capacities and needs. A longitudinal study is also recommended to explore the influence of the users' familiarity with the ARs affecting various aspects of interaction with the robot over time, as well as LoT preferences for specific LOAs.

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REFERENCES

[1] United Nations, *World Population Ageing 2020*. Population Division, Department of Economic and Social Affairs, 2020.

[2] A. A. Allaban, M. Wang, and T. Padir, "A systematic review of robotics research in support of in-home care for older adults," *Inf. MDPI*, vol. 11, no. 2, pp. 1–24, 2020.

[3] S. S. Honig, T. Oron-Gilad, H. Zaichyk, V. Sarne-Fleischmann, S. Olatunji, and Y. Edan, "Toward Socially Aware Person-Following Robots," *IEEE Trans. Cogn. Dev. Syst.*, vol. 10, no. 4, 2018.

[4] D. Katz, "Development of algorithms for a human-following robot," M.Sc. Thesis, Dept. of Industrial Engineering and Management, Ben-Gurion University of the Negev, Be'er Sheva, Israel, 2016.

[5] O. Avioz-Sarig, S. Olatunji, V. Sarne-Fleischmann, and Y. Edan, "Robotic system for physical training of older adults," *Int. J. Soc. Robot.*, pp. 1–16, 2020.

[6] M. Shishehgar, D. Kerr, and J. Blake, "A systematic review of research into how robotic technology can help older people," *Smart Health*, vol. 7–8. 2018.

[7] O. Zafrani and G. Nimrod, "Towards a holistic approach to studying human–robot interaction in later life," *Gerontologist*, vol. 59, no. 1, pp. e26–e36, Jan. 2019.

[8] G. Doisy, J. Meyer, S. Member, and Y. Edan, "The impact of human–robot interface design on the use of a learning robot system," *IEEE Trans. Human-Machine Syst.*, vol. 44, no. 6, pp. 788–795, 2014.

[9] R. Parasuraman and V. Riley, "Humans and automation: use, misuse, disuse, abuse," *Hum. Factors*, vol. 39, no. 2, pp. 230–253, 1997.

[10] S. J. Czaja, W. R. Boot, N. Charness, and W. A. Rogers, *Designing for older adults*, Third Edit. Taylor & Francis Group, 2019.

[11] T. B. Sheridan and W. L. Verplank, "Human and Computer Control of Undersea Teleoperators," *ManMachine Syst. Lab Dep. Mech. Eng. MIT Grant N0001477C0256*, no. DECEMBER 1978, p. 343, 1978.

[12] D. B. Kaber, "Issues in human-automation interaction modeling: Presumptive aspects of frameworks of types and levels of automation," *J. Cogn. Eng. Decis. Mak.*, vol. 12, no. 1, pp. 7–24, 2018.

[13] W. A. Olson and N. B. Sarter, "Management by consent in human-machine systems: When and why it breaks down," *Hum. Factors*, vol. 43, no. 2, pp. 255–266, 2001.

[14] M. R. Endsley, "From Here to Autonomy," *Hum. Factors*, vol. 59, no. 1, pp. 5–27, 2017.

[15] M. Vagia, A. A. Transeth, and S. A. Fjerdingen, "A literature review on the levels of automation during the years. What are the different taxonomies that have been proposed?," *Appl. Ergon.*, vol. 53, pp. 190–202, 2016.

[16] R. Parasuraman, T. B. Sheridan, and C. D. Wickens, "A model for types and levels of human interaction with automation," *IEEE Trans. Syst. Man, Cybern. - Part A Syst. Humans*, vol. 30, no. 3, pp. 286–297, 2000.

[17] B. Brehmer, "The dynamic OODA loop: Amalgamating Boyd's OODA loop and the cybernetic approach to command and control," in *Proceedings of the 10th international command and control research technology symposium*, 2005, pp. 365–368.

[18] J. Y. C. Chen, K. Procci, M. Boyce, J. Wright, A. Garcia, and M. J. Barnes, "Situation awareness–based agent transparency," no. April, pp. 1–29, 2014.

[19] T. Kim and P. Hinds, "Who should I blame? Effects of autonomy and transparency on attributions in human-robot interaction," in *Proceedings - IEEE International Workshop on Robot and Human Interactive Communication*, 2006, pp. 80–85.

[20] J. B. Lyons, "Being transparent about transparency: A model for human-robot interaction," *Trust Auton. Syst. Pap. from 2013 AAAI Spring Symp.*, pp. 48–53, 2013.

[21] D. Eizicovits, Y. Edan, I. Tabak, and S. Levy-Tzedek, "Robotic gaming prototype for upper limb exercise: Effects of age and embodiment on user preferences and movement," *Restor. Neurol. Neurosci.*, vol. 36, no. 2, pp. 261–274, 2018.

[22] R. Feingold Polak, A. Elishay, Y. Shahar, M. Stein, Y. Edan, and S. Levy-Tzedek, "Differences between young and old users when interacting with a humanoid robot: A qualitative usability study," *Paladyn, J. Behav. Robot.*, vol. 9, no. 1, pp. 183–192, 2018.

[23] S. Olatunji, N. Markfeld, D. Gutman, S. Givati, V. Sarne-Fleischmann, T. Oron-Gilad and Y. Edan "Improving the interaction of older adults with a socially assistive table setting robot," in *International Conference on Social Robotics*, 2019, pp. 568–577.

[24] K. J. Vicente and J. Rasmussen, "Ecological interface design: Theoretical foundations," *IEEE Trans. Syst. Man. Cybern.*, vol. 22, no. 4, pp. 589–606, 1992.

[25] J. M. Beer, S. Carolina, A. D. Fisk, and W. A. Rogers, "Toward a framework for levels of robot autonomy in human-robot interaction," *J. Human-Robot Interact.*, vol. 3, no. 2, pp. 74–99, 2014.

[26] G. Hoffman, "Evaluating Fluency in Human-Robot Collaboration," *IEEE Trans. Human-Machine Syst.*, vol. 49, no. 3, pp. 209–218, 2019.

[27] M. R. Endsley, "Toward a theory of situation awareness in dynamic systems," *Hum. Factors*, vol. 37, no. 1, pp. 32–65, Mar. 1995.

[28] J. Wachs, H. Stern, Y. Edan, M. Gillam, C. Feied, M. Smith and J. Handler, "Gestix: A doctor-computer sterile gesture interface for dynamic environments," *Adv. Soft Comput.*, vol. 39, pp. 30–39, 2007.

[29] G. Adamides, C. Katsanos, Y. Parmet, G. Christou, M. Xenos, T. Hadzilacos, and Y. Edan, "HRI usability evaluation of interaction modes for a teleoperated agricultural robotic sprayer," *Appl. Ergon.*, vol. 62, pp. 237–246, Jul. 2017.

[30] A. Jevtić, G. Doisy, Y. Parmet, and Y. Edan, "Comparison of Interaction Modalities for Mobile Indoor Robot Guidance: Direct Physical Interaction, Person Following, and Pointing Control," *IEEE Trans. Human-Machine Syst.*, vol. 45, no. 6, pp. 653–663, 2015.

[31] A. Theodorou, R. H. Wortham, J. J. Bryson, R. H. Wortham, and J. J. Bryson, "Designing and implementing transparency for real time inspection of autonomous robots inspection of autonomous robots," *Conn. Sci.*, vol. 29, no. 3, pp. 230–241, 2017.

[32] T. Inagaki, "Smart collaboration between humans and machines based on mutual understanding," *Annu. Rev. Control*, vol. 32, no. 2, pp. 253–261, Dec. 2008.

[33] S. Olatunji, T. Oron-Gilad, V. Sarne-Fleischmann, and Y. Edan, "User-centered feedback design in person-following robots for older adults," *Paladyn, J. Behav. Robot.*, vol. 11, no. 1, pp. 86–103, 2020.

[34] B. Robins, K. Dautenhahn, C. L. Nehaniv, N. A. Mirza, D. François, and L. Olsson, "Sustaining interaction dynamics and engagement in dyadic child-robot interaction kinesics: Lessons learnt from an exploratory study," *Proc. - IEEE Int. Work. Robot Hum. Interact. Commun.*, vol. 2005, pp. 716–722, 2005.

[35] L. J. Corrigan, C. Peters, D. Küster, and G. Castellano, "Engagement perception and generation for social robots and virtual agents," *Intell. Syst. Ref. Libr.*, vol. 105, pp. 29–51, 2016.

[36] G. Hoffman, "Evaluating Fluency in Human–Robot Collaboration," *IEEE Trans. Human-Machine Syst.*, vol. 49, no. 3, pp. 209–218, Jun. 2019.

[37] T. Hellström and S. Bensch, "Understandable robots - What, Why, and How," *Paladyn, J. Behav. Robot.*, vol. 9, no. 1, pp. 110–123, Jul. 2018.

[38] R. M. Taylor, "Situational Awareness Rating Technique (Sart): The Development of a Tool for Aircrew Systems Design," in *Situational Awareness*, Routledge, 2017, pp. 111–128.

[39] W. Wang, Y. Chen, R. Li, and Y. Jia, "Learning and Comfort in Human-Robot Interaction: A Review."

[40] C. M. Carpinella, A. B. Wyman, M. A. Perez, and S. J. Stroessner,

"The Robotic Social Attributes Scale (RoSAS)," in *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction - HRI '17*, 2017.
[41] A. Xu and G. Dudek, "Towards modeling real-time trust in asymmetric human–robot collaborations," in *Springer Tracts in Advanced Robotics*, 2016, vol. 114, pp. 113–129.
[42] K. Schaefer, "The Perception And Measurement Of Human- robot Trust," 2013.
[43] K. E. Schaefer, *Programming robots with ROS: A practical introduction to the robot operating system*, vol. 53. 2015.
[44] G. Doisy, A. Jevti, E. Lucet, and Y. Edan, "Adaptive Person-Following Algorithm Based on Depth Images and Mapping," in *IROS Workshop on Robot Motion Planning (Vol. 20, No. 12)*, 2012.
[45] S. S. Honig, D. Katz, T. Oron-Gilad, and Y. Edan, "The influence of following angle on performance metrics of a human-following robot," *25th IEEE Int. Symp. Robot Hum. Interact. Commun. RO-MAN 2016*, pp. 593–598, 2016.
[46] V. Sarne-Fleischmann, S. S. Honig, T. Oron-Gilad, and Y. Edan, "Proxemic preferences when being followed by a robot," *Isr. Minist. Sci. Technol. Rep.*, 2018.
[47] S. Olatunji, V. Sarne-Fleischmann, S. S. Honig, H. Zaichyk, M. Tamara, T. Oron-Gilad and Y. Edan, "User Preferences for socially acceptable person-following robots: environmental influence case studies," in *Assistance and Service Robotics in a Human Environment. A Workshop in conjunction with the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2018, no. September.
[48] S. Olatunji, V. Sarne-Fleischmann, S. S. Honig, T. Oron-Gilad, and Y. Edan, "Feedback design to improve interaction of person-following robots for older adults," in *Mobile Robot Assistants for the Elderly, Workshop at the IEEE International Conference on Robotics and Automation (ICRA)*, 2019.
[49] M. Ratchford and M. Barnhart, "Development and validation of the technology adoption propensity (TAP) index," *J. Bus. Res.*, vol. 65, no. 8, pp. 1209–1215, 2012.
[50] D. S. Syrdal, K. Dautenhahn, K. Koay, and M. L. Walters, "The negative attitudes towards robots scale and reactions to robot behaviour in a live human-robot interaction study," *23rd Conv. Soc. Study Artif. Intell. Simul. Behav. AISB*, pp. 109–115, 2009.
[51] N. Markfeld, "Feedback for human-robot collaboration," M.Sc. Thesis, Industrial Engineering and Management, Ben-Gurion University of the Negev, Beer Sheva, Israel, 2020.
[52] D. A. Norman, "How might people interact with agents," *Commun. ACM*, vol. 37, no. 7, pp. 68-- 71, 1994.
[53] S. A. Olatunji, "Socially Assistive Robots in Eldercare - Interaction Design for Varying Levels of Automation," Industrial Engineering and Management, Ben-Gurion University of the Negev, 2020.
[54] D. Gutman, "Levels of automation in human-robot collaboration," M.Sc. Thesis, Industrial Engineering and Management, Ben-Gurion University of the Negev, Beer Sheva, Israel, 2020.
[55] L. Foster and A. Walker, "Active and Successful Aging: A European Policy Perspective," *Gerontol.*, vol. 55, no. 1, 2015.

Chapter 6: Summary of results

The research went through three main stages to develop and empirically evaluate LoT, LOA, and LoT-LOA integrated models in different use cases using different robotic platforms as older adults interacted with the ARs. The study outcomes and how they interrelate to achieve the overarching thesis aims are summarized in Table 2 and detailed in the following sections.

Table 2: Summary of outcomes for the different research stages

Stages	Studies	Independent variable(s)	Task	Robot platform	Outcomes for design
Stage I LoT development (Chapter 3)	Study 1	Level of transparency and content of feedback	Person-following	Pioneer LX robot	Focus on **what** the robot is doing Feedback should include friendly content.
	Study 2	Mode of feedback			Use of a human voice at a slow pace
	Study 3	Timing of feedback			Continuous feedback at short intervals
	Study 4	Implemented feedback			Good feedback design improves user engagement, trust, and understanding.
Stage II LOA development (Chapter 4)	Study 5	LOA modes	Hazard perception	Modified Giraff telepresence robot	Lower LOA mode promotes more active control of the robot by the older adult.
	Study 6	LOA modes and task complexity			Significant interactions between the LOA modes and level of complexity of the task
Stage III LoT-LOA integration (Chapter 5)	Study 7	LoT and LOA modes	Person-following and table-setting	Pioneer LX robot and KUKA robot	There are LoT–LOA significant interaction effects using the aggregated metric. Combination of high LoT and low LOA increases engagement.

6.1. Summary of LoT Development – Stage I

Results from Study 1 which focused on identifying the preferred level of transparency and content of feedback revealed that *older adults preferred Level 1 LoT, i.e., information on **what** the robot is currently doing*. Regarding the feedback content, the preference was to *have information on the actions of the robot* and *some form of friendly content*. This includes specific information such as “starting”, “following”, “stopping”, and greetings from the robot. Study 2, which focused on identifying the preferred mode of feedback, revealed that voice feedback was preferred by the older adults over other forms of feedback. Good comprehension of the voice was facilitated by: a) a human voice and not a computer-simulated voice; b) a good audible female voice with a speech rate of less than 140 wpm; and c) adequate pauses at grammatical boundaries. Study 3, which focused on the timing of feedback revealed that *continuous feedback was more effective*, with preference for an interval of 5 seconds for a person-following robot that was behind the user. Study 4 evaluated the effect of the feedback design parameters on various aspects of the interaction. Results revealed that *good feedback design significantly and positively influenced users' engagement, understanding, and trust of the robot*. The outcome of these studies provided the design elements for the LoT model in Stage III. It also revealed the merits of a user-centered feedback design in assistive robotic developments to convey the required LoT which matches the perceptual demands of the target users.

6.2. Summary of LOA Development – Stage II

Results from Study 5, which was focused on evaluating the developed LOA modes with older adults, revealed that *older adults were able to control the robot effectively in both LOA modes*. They particularly enjoyed the dexterity with which the robot could be teleoperated in the lower LOA mode. The objective performance results showed that they were able to complete the subtasks given successfully in both LOA modes. Through the discussions with them at the end of the experiments, it was deduced that *they enjoyed the operation at the high LOA mode* in which the robot navigated autonomously towards the locations the user indicated. The usability, preference, and objective findings raised awareness towards areas of improvement in the LOA design that were useful insights for Stage III of the research. Evaluation of the LOA modes at different levels of complexity with younger adults in Study 6 revealed *significant interactions between the LOA modes and level of complexity of the task*. Results revealed that *performance improved at high LOAs when task complexity was low*. However, *when task complexity increased, lower LOAs improved performance*, perhaps because situation awareness and user involvement were higher, as observed in the results for workload and situation awareness. On the whole, the studies in this stage aided the characterization of the LOA modes developed which is helpful for implementation in other HRI contexts. The studies also yielded valuable insights into the critical aspects of the LOA design which should be incorporated in end-user interfaces to enhance the user experience and performance.

6.3. Summary of LoT-LOA Integration – Stage III

Results revealed the *importance of integrating LoTs with LOAs in the design of ARs supporting older adults*. The LoT–LOA integration as proposed was successfully implemented and tested in two test cases, providing evidence for the feasibility and viability of the design in ARs. LoT-LOA interaction effects were found in the test cases for the aggregated metric of interaction quality consisting of engagement, fluency, understanding, comfortability, and trust. The *combination of high LoT and low LOA was also found to increase engagement* in both test cases, which addressed the major challenge in Stage III. The significant results observed through the metrics proposed for evaluation of the LoT-LOA design revealed the potential of using these defined metrics for further assessment and benchmarking interaction quality of other HRI-related studies. This third stage, thus, coalesced the initial two stages of the research into an interaction design that prioritizes automation transparency and autonomy preferences in the design considerations. It contributed integral components into the interaction design guidelines presented in the concluding chapter for LOA–LoT designs in ARs that support older adults.

Chapter 7: General Discussion

This research focused on the interaction design of assistive robots that support older adults in utilitarian tasks related to levels of transparency, levels of automation, and their integration. The insights from the research are discussed along with recommendations.

7.1. Perception and preferences of the older adults

The perceptions of the older participants before and after the interaction with ARs were based on their responses to the Technology Adoption Propensity (TAP) index (Ratchford et al., 2012) and the Negative Attitude toward Robots Scale (NARS) (Syrdal et al., 2009) and are discussed as predispositions and post-interaction perceptions, respectively. In all the studies, older adult participants were generally confident to interact with the robots. This was seen in their willingness to participate in all the experiments after the explanations were given to them. This could have stemmed from the positive attitude most of them had towards technology, as seen in the TAP results, where most participants' responses reflected confidence in learning new technologies, trust in technology, and affirmation of the control and flexibility that the robots could provide them. This affirms previous findings (Chatterjee, 2021; Svendsen et al., 2013; Wu et al., 2017) which demonstrated that the initial positive attitude of users, such as openness to technology, is significantly correlated with willingness to interact with such technology.

Some of the participants had some form of negative perceptions for relying too much on the robot, even before the interaction, as seen in the NARS results. These opinions could have emanated from previous exposure to the shortfalls of overdependence on robots portrayed in the media in general (MacDorman et al., 2009) and through science fiction in books and movies (Soltan, 2019). In general, such negative affect can influence interactions with the robot, as noted before (Bishop et al., 2019). However, post-interaction questionnaire responses from the participants regarding their perception of the robot after the interaction revealed a sense of satisfaction contrary to the initial disposition beforehand. This confirms the predictions made by Nomura et al. (2004) regarding dissonance that may occur between perceptions before and after an interaction, owing to actual interaction with a real robot. This seemed to work out in the positive sense in the studies conducted in this research, as further revealed in the responses of the participants regarding willingness to interact with ARs on future occasions.

Age and gender significantly influenced the interactions with the AR. This was more evident during the feedback development phase where particular observations and outcomes were seen in certain age groups and by gender. For example, regarding engagement, the trend was that the oldest participants tended to be more engaged with the robot compared to their younger counterparts, as seen in the gaze duration analyses. This could be connected with the novelty effect where a larger percentage of the younger old adults may have been more familiar with some form of related technologies compared to the oldest participants (Zafrani et al., 2019). This could inspire more attraction to the robot, and thus engage them more. These findings are in line with previous findings (Bishop et al., 2019), where it was shown that familiarity with related technology negatively correlated with the intention to interact with a robot. There were also age-group differences with regard to understanding and trust, as seen in the results (Chapter 3, Section 7.2.7). Even though the user-centered design perspective aimed to satisfy the needs and expectations of different age groups, some of these differences point to areas where further investigation should be made for improvements.

Gender was found in previous studies to have a significant influence on the interaction with a robot (Heerink, 2011). This was confirmed, particularly in the first stage of the research where female participants tended to be more engaged with the robot than the males and seemed to ask more questions to clarify their understanding of the robot better. Female participants also seemed to trust the robot more, as seen in the time they waited for the robot (see Chapter 3, Section 7.2.7). They seemed to trust that the robot would perform correctly even when it delayed or lost track. Even though Heerink (2011) and de Graff et al. (2013) associated anxiety with female interaction with a robot, the current study agrees with earlier findings by Shibata et al. (2009) which found that females are more comfortable around robots. This could potentially influence trust positively. Several reasons could be responsible for this disparity, which includes the context and type of robot. However, the reasons cannot fully be established from this study due to the limited sample. Still, it highlights the need to further explore the expectations and needs of the different genders such that the feedback design could be tuned to meet possible gender preferences.

7.2. Influence of Levels of Transparency

Results revealed that the older adults preferred current and immediate information on what the robot was doing (LoT 1; what) over other levels of transparency (why, what is next). They were satisfied with the robot communicating just its current actions and status information without the need to present all information. They also seemed to trust that the robot would know how to handle itself if more information were available or if the state of matters would change, despite their initial disposition to the robot as revealed in the NARS index. This agrees with the discussions in Wortham et al. (2017), who hypothesized that users may prefer less information based on the degree of trust they have developed in the system. The older adults' preference concurs with the design principles for transparency outlined in Lyons (2013), where designers were cautioned regarding providing too much information to users. It was emphasized that if such information exceeded the preferences and needs of the users, it could create frustration and/or confusion. It also agrees with previous findings (Doisy et al., 2014) which noted that providing too much information resulted in an information overload and decreased users' performance.

During the experiments, participants were asked to suggest additional information that they would like the robot to provide. This was to make room for participants' preferences on other aspects of transparency relating to the robot (such as information on how the robot makes its decisions) and environment (such as information on constraints and safety-related cautions). Care was taken to avoid overloading the participants with too many transparency options. Therefore, transparency models connected with teamwork (information on the role of the robot and human in task performance) and human state (information regarding physical, emotional, or stress state of the participant) were not mentioned. Participants' responses regarding specific content they would like indicated revealed that they were interested in task-related transparency information (such as "following" and "stopping" in the person-following experiment, "starting to set the table" in the table-setting task, and "locating the room to navigate to" in the telepresence task). Additionally, some participants wanted the robot to ask about their well-being ("greetings", "How are you?"). These are aspects of the human-related model of transparency that participants provided without being directly asked. This supports the significance of "thinking aloud" sessions recommended in user-centered system design (Fong et al., 2001). The preference for greetings also supports the finding of Sabelli et al. (2011). Some of these preferences were incorporated in the integration design performed in Study 3.

There was an interesting contrast in the LoT demands of younger and older adults. In a previous user study (Sanders et al., 2014), in which younger adults (aged 18–22) participated to examine the effect of transparency and feedback modality on trust, they preferred higher LoTs. This may not only have been an age-related trust issue, but may also relate to the robot's embodiment. In that study, the robot was simulated on a computer desktop and not physically present, as in the current studies. This suggests that interacting with a physical robot and observing its performance may have a stronger effect on users' trust, and affect the amount of information (LoT) the user may prefer the robot to provide. This may also highlight that older adults' needs are specific, as they are aware of their physical and cognitive deficiencies (such as having slower reactions than when they were younger).

The population addressed in Studies 1–3 of Stage I may be unique in their LoT demands, but we cannot assure this claim. To some degree, participants were part of a convenience sample, and the requirement to come to the lab may have even further separated them from other older adults, as our participants were generally positive towards technology and motivated to come to the university for the experiments. To establish a stronger mapping between the preferences in this study and that of a wider population of older adults, more extensive studies are recommended, as suggested by Mutlu and colleagues (Porfirio et al., 2019). These further studies would assess the external validity of this outcome on a larger scale. Studies that examine the possible changes in users' transparency demands, such as trust and comfortability adaptation for interacting with a robot, occur over longer periods of interaction.

7.3. Influence of Levels of Automation

Results emanating from the test of the LOA modes across all the test cases indicate that the older adults were able to effectively accomplish the defined tasks using both LOA modes. This highlights the learnability and ease of use of these modes. In general, older adults particularly preferred to be more involved and active in all the test cases as they collaborated with the robot. They therefore indicated interest in the low LOA mode. Responses in the questionnaires and discussions reflected that they considered a low LOA as an invitation by the robot to collaborate on tasks, as opposed to a high LOA where they seemed to perceive the AR as more independent. However, further discussions with the participants also revealed that they could attend to more tasks concurrently if the robot was operating in the high LOA mode. This agrees with the literature on the possibility of increasing LOAs to extend users' capabilities (Endsley, 2017). Overall, it reveals the potential for older adult users utilizing the systems in alternative LOA modes to accomplish specific tasks or subtasks, which is one of the objectives of introducing alternative robot autonomy levels (Kaber & Endsley, 1997).

The developed LOA modes were also evaluated with younger adults, who, in the role of caregivers, performed the telepresence tasks similarly to the older adults, but with different levels of complexity. The influence of the implemented LOA modes was observed between the different task complexity levels. Previous studies (Wickens et al., 2010; Onnasch et al., 2014), involving expert and non-expert users, revealed an overall improvement in performance with increasing automation for routine tasks. However, in tasks with more situational demands, critical decisions, and action implementation, performance declined with higher automation.

These findings can be associated with the situations introduced in Study 6 in which the higher LOA produced higher performance in the lower complexity (and less demanding) task. In the high complexity task, which demanded more critical decisions and actions and in which more automation failures occurred, the lower LOA yielded higher performance. An increase in workload was observed as the task complexity increased while using the high LOA mode. This may be related to the frustration experienced by the participants in the higher task complexity when the automation failed or did not perform as expected (as seen in the frustration dimension of the NASA-TLX).

Switching between LOA modes was also evaluated in the telepresence task (in Study 6). In some of the situations where there were challenges in performing the task, participants switched to a lower automation level, perhaps to facilitate easier handling of some of these challenges as noted in Olatunji et al. (2019), where a lower LOA was found to better facilitate easier interaction. The switching, however, incurs some switch costs (Kaber, 2018; Wylie et al., 2000), which may have contributed to the reason why most of the participants did not switch when the task complexity was low. Consistent with previous findings that lower LOA tends to improve the SA of users (Endsley et al., 1995; Onnasch et al., 2014), in the low complexity task, the low LOA mode appeared to provide better situation awareness in terms of focus of attention and the information participants gained about the environment.

These observations concur with the view of Kaber (2018), arguing that the outcome of LOA implementations may vary with different task demands, and advocating for the characterization of these LOA models in different tasks, contexts, and situations in order to collate the prevalent trends for model improvements. Therefore, we recommend that the evaluation of these LOA modes with different levels of complexity also be tested with older adults as extended usability studies in other test cases and environments. Future work should address more systematic situations where the robot is closer to its operational boundaries and likely to require more support from the user (interchangeable LOAs), as these are types of situations where dynamic changes can occur all the time (e.g., placement of objects, unidentified objects, etc.), especially in unstructured environments like homes.

7.4. Integration of LoT and LOA

LoT-LOA interaction effects were found in the test cases for the aggregated metric, and particularly for engagement. Combining a high LoT (which provides more information) with a low LOA (which promotes higher engagement) improved the interaction. Previous research has indicated that in high LOAs, users can become frustrated due to the lack of control they sometimes feel (Norman, 1994). More frustration can ensue if users are not aware of what is happening (Kim et al., 2006). Therefore, providing a higher degree of control (through a low LOA) and higher transparency (through a high LoT) can minimize these potential challenges when older adults interact with their ARs. This also corresponds with previous recommendations for enhanced interaction design that aim to improve the sense of control in the automation (Norman, 1994) and transparency in the robot's actions (Kim et al., 2006).

Combining high LoT with low LOA as a behaviour of the AR appealed more to the older adults as a companion supporting them rather than as a tool carrying out house chores in isolation. These results are in line with previous studies in which designs related to the LoT and LOA designs were investigated for similar tasks with young adults as participants (Gutman, 2020; Olatunji et al., 2018). However, it seemed that younger adults preferred the higher LOA mode irrespective of the LoT mode, while the older adults preferred the lower LOA that allowed them more engagement with the task. Further research should investigate more into this, and whether this pattern will change over time as older adults gain more familiarity with ARs.

There were also task-related factors that influenced specific aspects of the interaction such as fluency, understanding, and comfortability. This could be because of the differences in workload demands of different tasks, feedback modality conditions, and also the position of the user relative to the robot. However, these claims cannot be affirmed since the study did not specifically set out to examine the interaction effect of these factors. It does highlight the significance of looking at other task-related factors such as the role of the robot in the task, the relevance of the task to the user, and the frequency of the interaction, as proposed in Honig et al. (2018).

7.5. Interaction design implications

The satisfactory interaction of the older adult with the ARs in both cases using the implemented model met the expectations regarding the potential benefits of shared control and information sharing. This contributes to active physical and cognitive involvement which are important to encourage successful aging for older adults (Foster et al., 2015). The combination of objective and subjective elements used as metrics for the evaluation also forecasts their use as a standard in HRI evaluation.

It is recommended to include an introductory session with the robot before the interaction to better prepare an older adult. The feedback design parameters and interfaces should include user-friendly initial introductions before the actual task implementation with the robot. The user should also be given the option to skip this session if they are already familiar with the robot so that this introduction session does not induce boredom in the interaction. Such a session provides more familiarity with the robot as the participant spends some more time interacting with the robot (Šabanovic et al., 2013), and it also provides some basic training to ensure that the focus is on the specific study parameters.

Chapter 8: Conclusions

8.1. Take away messages

Interaction design guidelines of ARs that support older adults related to LoTs and LOAs:

- Ensure that the robot constantly provides sufficient information on what it is doing (LoT level 1) through a feedback mode that is applicable to the specific task at hand.
- Operate the robot at a low LOA to keep the older adult more actively involved in the task.
- Combine a low LOA with a high LoT to maintain older adults' awareness of the robot's operations without overloading them with information.
- Adapt LoTs for the specific LOA to ensure that the robot's actions match the older adults' expectations.

8.2. Limitations

The recommendations made in this thesis are based on three robotic test cases with three different types of robots and tasks; outcomes and recommendations may vary for other test cases.

The older adults who participated in the user studies were mostly in the younger-old (65 to 74 years) and old-old (75 to 84 years) groupings; therefore, results relate only to these age groups. Only some of the participants were in the group of the oldest-old (85 years and above). There may be some differences if the evaluations are performed with participants from other age groups. We expect that results would be amplified for the higher age groups.

All the participants were mostly healthy older adults who were physically and cognitively fit. They came independently to the labs for experiments. Neither specific health status records or information regarding physical or mental needs were collected from individual participants. Thus, there may have been some changes in the procedure for the experiments if there had been physically or mentally challenged groups of older adults among the participants. Also, some of the design parameters that resulted as outcomes might differ if the evaluations were tailored for and carried out with participants with specific health needs.

Only two main cultural perspectives were considered: Israeli and Swedish older adult populations. Different studies have shown that cultural values have a significant effect on perceptions of robots (Bartneck et al., 2005; Libin et al., 2008). Therefore, there is some possibility that there could be variations in the perceptions and preferences of the older adults presented in this thesis if the models were evaluated with older adults with a different cultural background.

Moreover, the evaluations were carried out for single task scenarios. The design was not evaluated in multiple task situations with other factors such as varying levels of complexity of these multi-task situations. This could bring more variations into the design settings and outcome, particularly in a more demanding task environment that may be prone to more uncertainties or limitations of the robotic system. Evaluation of the interaction design parameters was also carried out for relatively short periods of the experiments within well-defined laboratory settings. Some outcomes may have been different if the context were in an actual home environment with the complexities of dynamic changes in that environment.

8.3. Future work

Future work should assess the robustness of the LoT-LOA design for different tasks, robotic systems, and environmental factors, with consideration of a variety of human and interaction variables. This will constitute a framework for the assessment of the quality of interaction (QoI) of older adults with the ARs. The details of these different variables that could be assessed for the development of a holistic QoI framework are detailed as follows:

Task variables: Evaluations should include other utilitarian tasks involved in eldercare such as other housekeeping tasks or tasks involving interaction with other environments such shopping. Tasks in other categories of daily living activities such as ADLs and EADLs should also be considered. This would further evaluate the feasibility of implementing the model in other tasks and highlight aspects where adjustments may need to be made to suit specific tasks. In addition, more investigation regarding other forms of task complexities and uncertainties that could occur in multi-task scenarios should be considered.

Environment-related variables: Evaluations should be performed for extended periods of time in the homes of older adults to assess their preferences as the novelty effect wears off. This would constitute various environmental influences such as obstacles in the environment, noise challenges, illumination differences, space constraints, and other clutter considerations. It would also provide the opportunity to evaluate the system with considerations of other users or bystanders who also share the house.

Robot-related variables: All the test cases were normal functioning robotic systems with fairly optimal performance in all the test cases and scenarios. The interaction design should, however, also be tested in situations of degraded performance, where malfunctions test the applicability and relevance of the LoT-LOA integrated model. Further investigations should include other robotic platforms such as humanoid robots, mobile manipulators, and even a team of robots working together. These could raise other considerations that the scope of this work did not cover, but for which the outcome of the current research could provide a basis for advancement.

Human-related variables: Further investigations with older adults should include the oldest-old group and groups with varying physical or mental capacities and needs. This may involve some adjustment in the method for interaction with the AR as applicable for specific needs. It may also highlight certain aspects of the interaction, benefits, or shortfalls of the design for further improvement. Influence of gender and age category of the older adult users should also be further investigated in order to meet the specific needs of the different groups that make up the older adult population. Other differences resulting from cultural, professional, socio-economic, and technical backgrounds should also be considered.

Interaction-related: Model evaluation is recommended in users' homes over extended periods of time to investigate interaction-related factors. These factors include persuasiveness without overriding the preferences and privacy of older adults; appropriateness of the interaction which incorporates social values such as respect, politeness, and responsibility; engagement, and disengagement for maintaining the interaction; and use and disuse along time.

These are crucial factors that should be considered in future work to improve the robustness of the design and the development of a framework that considers most of the factors related to the assessment of the quality of interaction of older adults with ARs.

References

Adamides, G., Katsanos, C., Parmet, Y., Christou, G., Xenos, M., Hadzilacos, T., & Edan, Y. (2017). HRI usability evaluation of interaction modes for a teleoperated agricultural robotic sprayer. *Applied Ergonomics*, *62*, 237–246. https://doi.org/10.1016/j.apergo.2017.03.008

Allaban, A. A., Wang, M., & Padir, T. (2020). A systematic review of robotics research in support of in-home care for older adults. *Information MDPI*, *11*(2), 1–24. https://doi.org/10.3390/info11020075

Avioz-Sarig, O. (2019). *Feedback in Robotic System for Physical Training of Older Adults* (Issue September). M.Sc. Thesis, Industrial Engineering and Management.

Avioz-Sarig, O., Olatunji, S., Sarne-Fleischmann, V., & Edan, Y. (2020). Robotic System for Physical Training of Older Adults. *International Journal of Social Robotics*, 1–16. https://doi.org/10.1007/s12369-020-00697-y

Bartneck, C., Nomura, T., Kanda, T., Suzuki, T., & Kato, K. (2005). Cultural differences in attitudes towards robots. *AISB'05 Convention: Social Intelligence and Interaction in Animals, Robots and Agents - Proceedings of the Symposium on Robot Companions: Hard Problems and Open Challenges in Robot-Human Interaction*, 1–4.

Beer, J., Fisk, A. D., & Rogers, W. A. (2014). Toward a Framework for Levels of Robot Autonomy in Human-Robot Interaction. *Journal of Human-Robot Interaction*, *3*(2), 74. https://doi.org/10.5898/JHRI.3.2.Beer

Berenstein, R., & Edan, Y. (2017). Human-robot collaborative site-specific sprayer. *Journal of Field Robotics*, *34*(8), 1519–1530. https://doi.org/10.1002/rob.21730

Bishop, L., Maris, A. Van, Dogramadzi, S., & Zook, N. (2019). Social robots : The influence of human and robot characteristics on acceptance. *Paladyn, Journal of Behavioral Robotics*, *10*(1), 346–358.

Bogue, R. (2013). Robots to aid the disabled and the elderly. *Industrial Robot: An International Journal*, *40*(6), 519–524. https://doi.org/10.1108/IR-07-2013-372

Brehmer, B. (2005). The dynamic OODA loop: Amalgamating Boyd's OODA loop and the cybernetic approach to command and control. *Proceedings of the 10th International Command and Control Research Technology Symposium*, 365–368.

Broniatowska, P. (2019). Population Ageing and Inflation. *Journal of Population Ageing*, *12*(2), 179–193. https://doi.org/10.1007/s12062-017-9209-z

Carpinella, C. M., Wyman, A. B., Perez, M. A., & Stroessner, S. J. (2017). The Robotic Social Attributes Scale (RoSAS). *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction - HRI '17*. https://doi.org/10.1145/2909824.3020208

Chatterjee, S. (2021). *User-Experience Design of a Personal Robot Arm* (Issue March). PhD Thesis, Department of Industrial Engineering and Management, Ben-Gurion University of the Negev, Israel.

Chen, J. Y. C., Procci, K., Boyce, M., Wright, J., Garcia, A., & Barnes, M. J. (2014). Situation awareness–based agent transparency. *Army Research Lab Aberdeen Proving Ground Md Human Research and Engineering*, *April*, 1–29.

Chernbumroong, S., Cang, S., Atkins, A., & Yu, H. (2013). Elderly activities recognition and classification for applications in assisted living. *Expert Systems with Applications*, *40*(5), 1662–1674. https://doi.org/10.1016/j.eswa.2012.09.004

Corrigan, L. J., Peters, C., Küster, D., & Castellano, G. (2016). Engagement perception and generation for social robots and virtual agents. *Intelligent Systems Reference Library*, *105*, 29–51. https://doi.org/10.1007/978-3-319-31056-5_4

Czaja, S. J., Boot, W. R., Charness, N., & Rogers, W. A. (2019). *Designing for older adults* (C. Press (ed.); Third Edit). Taylor & Francis Group.

Czaja, S. J., Boot, W. R., Charness, N., Rogers, W. A., Boot, W. R., Charness, N., & Rogers, W. A. (2019). *Designing for Older Adults* (Third Edit). CRC Press. https://doi.org/10.1201/b22189

De Graaf, M. M. A., & Ben Allouch, S. (2013). Exploring influencing variables for the acceptance of social robots. *Robotics and Autonomous Systems*, *61*(12), 1476–1486. https://doi.org/10.1016/j.robot.2013.07.007

Dekker, S. W. A., & Woods, D. D. (2002). MABA-MABA or Abracadabra? Progress on Human-Automation Co-ordination. *Cognition, Technology & Work*, *4*(4), 240–244. https://doi.org/10.1007/s101110200022

Doisy, G., Meyer, J., Member, S., & Edan, Y. (2014). The impact of human–robot interface design on the use of a learning robot system. *IEEE Transactions on Human-Machine Systems*, *44*(6), 788–795. https://doi.org/10.1109/THMS.2014.2331618

Draper, J. V. (1995). Teleoperators for advanced manufacturing: Applications and human factors challenges. *International Journal of Human Factors in Manufacturing*, *5*(1), 53–85. https://doi.org/10.1002/hfm.4530050105

Eizicovits, D., Edan, Y., Tabak, I., & Levy-Tzedek, S. (2018). Robotic gaming prototype for upper limb exercise: effects of age and embodiment on user preferences and movement. *Restorative Neurology and Neuroscience*, *36*(2), 261–274. https://doi.org/10.3233/RNN-170802

En, L. Q., & Lan, S. S. (2011). The applicability of gricean maxims in social robotics polite dialogue. *6th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, 195–196.

Endsley, M. (1995). Toward a theory of Situation Awareness in Dynamic Systems. *Human Factors*, *37*(1), 32–64. https://doi.org/10.1518/001872095779049543

Endsley, M., & Kiris, E. O. (1995). The Out-of-the-Loop Performance Problem and Level of Control in Automation. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *37*(2), 381–394. https://doi.org/10.1518/001872095779064555

Endsley, M. R., & Kaber, D. B. (1999). Level of automation effects on performance, situation awareness and workload in a dynamic control task. In *Ergonomics* (Vol. 42, Issue 3). https://doi.org/10.1080/001401399185595

Fasola, J., & Mataric, M. (2013). A Socially Assistive Robot Exercise Coach for the Elderly. *Journal of Human-Robot Interaction*, *2*(2), 3–32. https://doi.org/10.5898/JHRI.2.2.Fasola

Feingold-Polak, R., Elishay, A., Shahar, Y., Stein, M., Edan, Y., & Levy-Tzedek, S. (2018). Differences between young and old users when interacting with a humanoid robot: A qualitative usability study. *Paladyn, Journal of Behavioral Robotics*, *9*(1), 183–192. https://doi.org/10.1145/3173386.3177046

Fiorini, L., De Mul, M., Fabbricotti, I., Limosani, R., Vitanza, A., D'Onofrio, G., Tsui, M., Sancarlo, D., Giuliani, F., Greco, A., Guiot, D., Senges, E., & Cavallo, F. (2019). Assistive robots to improve the independent living of older persons: results from a needs study. *Disability and Rehabilitation: Assistive Technology*, 1–11. https://doi.org/10.1080/17483107.2019.1642392

Fischinger, D., Einramhof, P., Papoutsakis, K., Wohlkinger, W., Mayer, P., Panek, P., Hofmann, S., Koertner, T., Weiss, A., Argyros, A., & Vincze, M. (2016). Hobbit, a care robot supporting independent living at home: first prototype and lessons learned. *Robotics and Autonomous Systems*, *75*, 60–78. https://doi.org/10.1016/j.robot.2014.09.029

Flemisch, F., Heesen, M., Hesse, T., Kelsch, J., Schieben, A., & Beller, J. (2012). Towards a dynamic balance between humans and automation: Authority, ability, responsibility and control in shared and cooperative control situations. *Cognition, Technology and Work*, *14*(1), 3–18. https://doi.org/10.1007/s10111-011-0191-6

Fong, T., Cabrol, N., Thorpe, C., & Baur, C. (2001). A Personal User Interface for Collaborative Human-Robot Exploration. *International Symposium on Artificial Intelligence, Robotics and Automation in Space, June 2001, Montreal, Canada*, *February 1999*.

Foster, L., & Walker, A. (2015). Active and Successful Aging: A European Policy Perspective. *The Gerontologist, 55*(1). https://doi.org/10.1093/geront/gnu028

Frennert, S., Aminoff, H., & Östlund, B. (2020). Technological Frames and Care Robots in Eldercare. *International Journal of Social Robotics*, *February*. https://doi.org/10.1007/s12369-020-00641-0

Goetze, S., Fischer, S., Moritz, N., Appell, J.-E., Wallhoff, F., & et Al., S. G. (2012). Multimodal Human-Machine Interaction for Service Robots in Home-Care Environments. *In Proceedings of the 1st Workshop on Speech and Multimodal Interaction in Assistive Environments, Association for Computational Linguistics*, *July*, 1–7.

Góngora, A. S., Hamrioui, S., de la Torre Díez, I., Motta Cruz, E., López-Coronado, M., & Franco, M. (2019). Social Robots for People with Aging and Dementia: A Systematic

Review of Literature. *Telemedicine and E-Health*, *25*(7), 533–540. https://doi.org/10.1089/tmj.2018.0051

Gross, H. M., Scheidig, A., Debes, K., Einhorn, E., Eisenbach, M., Mueller, S., Schmiedel, T., Trinh, T. Q., Weinrich, C., Wengefeld, T., Bley, A., & Martin, C. (2017). ROREAS: robot coach for walking and orientation training in clinical post-stroke rehabilitation - prototype implementation and evaluation in field trials. *Autonomous Robots*, *41*(3), 679–698. https://doi.org/10.1007/s10514-016-9552-6

Gutman, D. (2020). *Levels of automation in human-robot collaboration*. M.Sc. Thesis, Industrial Engineering and Management, Ben-Gurion University of the Negev, Beer Sheva, Israel.

Gutman, D., Olatunji, S., Givati, S., Sarne-Fleischmann, V., Oron-Gilad, T., & Edan, Y. (2020). Evaluating levels of automation and feedback in an assistive robotic table clearing task for eldercare. *Personal Communications -Dept. of Industrial Engineering and Management, Ben-Gurion University of the Negev, Be'er-Sheva 8410501, Israel.*

H.P. Grice. (1989). Logic and conversation. *Studies in the Ways of Words*, 22–40.

Hall, A. K., Backonja, U., Painter, I., Cakmak, M., Sung, M., Lau, T., Thompson, H. J., & Demiris, G. (2019). Acceptance and perceived usefulness of robots to assist with activities of daily living and healthcare tasks. *Assistive Technology*, *31*(3), 133–140. https://doi.org/10.1080/10400435.2017.1396565

Heerink, M. (2011). Exploring the influence of age, gender, education and computer experience on robot acceptance by older adults. *HRI 2011 - Proceedings of the 6th ACM/IEEE International Conference on Human-Robot Interaction*, 147–148. https://doi.org/10.1145/1957656.1957704

Hellström, T., & Bensch, S. (2018). Understandable robots - what, why, and how. *Paladyn, Journal of Behavioral Robotics*, *9*(1), 110–123. https://doi.org/10.1515/pjbr-2018-0009

Hocraffer, A., & Nam, C. S. (2017). A meta-analysis of human-system interfaces in unmanned aerial vehicle (UAV) swarm management. *Applied Ergonomics*, *58*, 66–80. https://doi.org/10.1016/j.apergo.2016.05.011

Hoffman, G. (2019a). Evaluating Fluency in Human-Robot Collaboration. *IEEE Transactions on Human-Machine Systems*, *49*(3), 209–218. https://doi.org/10.1109/THMS.2019.2904558

Hoffman, G. (2019b). Evaluating Fluency in Human–Robot Collaboration. *IEEE Transactions on Human-Machine Systems*, *49*(3), 209–218. https://doi.org/10.1109/THMS.2019.2904558

Honig, S. S., Oron-Gilad, T., Zaichyk, H., Sarne-Fleischmann, V., Olatunji, S., & Edan, Y. (2018). Toward Socially Aware Person-Following Robots. *IEEE Transactions on Cognitive and Developmental Systems*, *10*(4). https://doi.org/10.1109/TCDS.2018.2825641

Huber, A., Lammer, L., Weiss, A., & Vincze, M. (2014). Designing Adaptive Roles for Socially Assistive Robots: A New Method to Reduce Technological Determinism and Role Stereotypes. *Journal of Human-Robot Interaction*, *3*(2), 100. https://doi.org/10.5898/jhri.3.2.huber

Inagaki, T. (2008). Smart collaboration between humans and machines based on mutual understanding. *Annual Reviews in Control*, *32*(2), 253–261. https://doi.org/10.1016/J.ARCONTROL.2008.07.003

Jevtić, A., Doisy, G., Parmet, Y., & Edan, Y. (2015). Comparison of Interaction Modalities for Mobile Indoor Robot Guidance: Direct Physical Interaction, Person Following, and Pointing Control. *IEEE Transactions on Human-Machine Systems*, *45*(6), 653–663. https://doi.org/10.1109/THMS.2015.2461683

Jipp, M. (2014). Levels of automation: effects of individual differences on wheelchair control performance and user acceptance. *Theoretical Issues in Ergonomics Science*, *15*(5), 479–504. https://doi.org/10.1080/1463922X.2013.815829

Kaber, D. B. (2018). Issues in human-automation interaction modeling: Presumptive aspects of frameworks of types and levels of automation. *Journal of Cognitive Engineering and Decision Making*, *12*(1), 7–24. https://doi.org/10.1177/1555343417737203

Kaber, D. B., Onal, E., & Endsley, M. R. (2000). Design of automation for telerobots and the effect on performance, operator situation awareness, and subjective workload. *Human*

Factors and Ergonomics in Manufacturing, *10*(4), 409–430. https://doi.org/10.1002/1520-6564(200023)10:4<409::aid-hfm4>3.3.co;2-m

Kachouie, R., Sedighadeli, S., & Abkenar, A. B. (2017). The role of socially assistive robots in elderly wellbeing: a systematic review. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 10281, pp. 669–682). Springer Verlag. https://doi.org/10.1007/978-3-319-57931-3_54

Khosla, R., & Chu, M.-T. (2013). Embodying care in Matilda: an affective communication robot for emotional wellbeing of older people in Australian residential care facilities. *ACM Transactions on Management Information Systems (TMIS)*, *4*(4), 18. https://doi.org/10.1145/2544104

Kim, T., & Hinds, P. (2006). Who should I blame? Effects of autonomy and transparency on attributions in human-robot interaction. *Proceedings - IEEE International Workshop on Robot and Human Interactive Communication*, 80–85. https://doi.org/10.1109/ROMAN.2006.314398

Kuo, Y. P., Pai, N. S., Hsieh, H. H., & Kuo, C. L. (2013). The application of CMAC-based fall detection in Omni-directional mobile robot. *2013 International Conference on Advanced Robotics and Intelligent Systems, ARIS 2013 - Conference Proceedings*, 64–69. https://doi.org/10.1109/ARIS.2013.6573536

Lee, J., & Moray, N. (1992). Trust, control strategies and allocation of function in human-machine systems. *Ergonomics*, *35*(10), 1243–1270. https://doi.org/10.1080/00140139208967392

Leite, I., Martinho, C., & Paiva, A. (2013). Social Robots for Long-Term Interaction: A Survey. *International Journal of Social Robotics*, *5*(2). https://doi.org/10.1007/s12369-013-0178-y

Libin, A. V, & Libin, E. V. (2008). Person – Robot Interactions From the Robopsychologists ' Point of View : The Robotic Psychology and Robotherapy Approach. *Proceedings of the IEEE*, *92*(11), 1789–1803.

Lyons, J. B. (2013). Being transparent about transparency: A model for human-robot interaction. *Trust and Autonomous Systems: Papers from the 2013 AAAI Spring Symposium*, 48–53.

MacDorman, K. F., Vasudevan, S. K., & Ho, C. C. (2009). Does Japan really have robot mania? Comparing attitudes by implicit and explicit measures. *AI and Society*, *23*(4), 485–510. https://doi.org/10.1007/s00146-008-0181-2

Markfeld, N. (2020). *Feedback for human-robot collaboration*. M.Sc. Thesis, Industrial Engineering and Management, Ben-Gurion University of the Negev, Beer Sheva, Israel.

Markfeld, N., Olatunji, S., & Edan, Y. (2020). Exploring Feedback Modalities in a Mobile Robot for Telecare. *Personal Communications -Dept. of Industrial Engineering and Management, Ben-Gurion University of the Negev, Be'er-Sheva 8410501, Israel.*

Markfeld, N., Olatunji, S., Gutman, D., Givati, S., Sarne-Fleischmann, V., & Edan, Y. (2019). Feedback modalities for a table setting robot assistant for elder care. *Quality of Interaction in Socially Assistive Robots, Quality of Interaction in Socially Assistive Robots (QISAR) Workshop International Conference on Social Robotics (ICSR'19) - Madrid, Spain, November 26-29, 2019*, 3–8.

McColl, D., Louie, W. Y. G., & Nejat, G. (2013). Brian 2.1: A socially assistive robot for the elderly and cognitively impaired. *IEEE Robotics and Automation Magazine*, *20*(1), 74–83. https://doi.org/10.1109/MRA.2012.2229939

Mitzner, T. L., Chen, T. L., Kemp, C. C., & Rogers, W. A. (2014). Identifying the Potential for Robotics to Assist Older Adults in Different Living Environments. *International Journal of Social Robotics*, *6*(2). https://doi.org/10.1007/s12369-013-0218-7

Mitzner, T. L., Smarr, C. A., Rogers, W. A., & Fisk, A. D. (2015). Adult's perceptual abilities. In *The Cambridge Handbook of Applied Perception Research* (pp. 1051–1079).

Ms, A. Y., Masuda, R., & Kanagawa, H. (2012). Autonomous foods handling by chopsticks for meal assistant robot. *ROBOTIK 2012; 7th German Conference on Robotics*, 221–226.

Nomura, T., Kanda, T., Suzuki, T., & Kato, K. (2004). Psychology in human-robot communication: An attempt through investigation of negative attitudes and anxiety toward robots. ... *Communication*, 35–40. https://doi.org/10.1109/ROMAN.2004.1374726

Norman, D. A. (1994). How might people interact with agents. *Communications of the ACM*, *37*(7), 68-- 71.

Olatunji, S., Markfeld, N., Gutman, D., Givati, S., Sarne-Fleischmann, V., Oron-Gilad, T., & Edan, Y. (2019). Improving the Interaction of Older Adults with a Socially Assistive Table Setting Robot. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 11876 LNAI*. https://doi.org/10.1007/978-3-030-35888-4_53

Olatunji, S., Oron-Gilad, T., & Edan, Y. (2018). Increasing the Understanding between a Dining Table Robot Assistant and the User. *International Ph.D. Conference On Safe and Social Robotics, Madrid*. http://www.socrates-project.eu/internal-documents/SSR_2018/SSR_2018_paper_24.pdf

Olatunji, S., Oron-Gilad, T., Sarne-Fleischmann, V., & Edan, Y. (2020). User-centered feedback design in person-following robots for older adults. *Paladyn, Journal of Behavioral Robotics*, *11*(1), 86–103. https://doi.org/https://doi.org/10.1515/pjbr-2020-0007

Olatunji, S., Sarne-Fleischmann, V., Honig, S. S., Oron-Gilad, T., & Edan, Y. (2019). Feedback design to improve interaction of person-following robots for older adults. *Mobile Robot Assistants for the Elderly, Workshop at the IEEE International Conference on Robotics and Automation (ICRA)*.

Olatunji, S., Sarne-Fleischmann, V., Honig, S. S., Zaichyk, H., Tamara, M., Oron-Gilad, T., & Edan, Y. (2018). User preferences for socially acceptable person-following robots: environmental influence case studies. *Assistance and Service Robotics in a Human Environment. A Workshop in Conjunction with the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems*, *September*.

Olson, W. A., & Sarter, N. B. (2001). Management by consent in human-machine systems: When and why it breaks down. *Human Factors*, *43*(2), 255–266. https://doi.org/10.1518/001872001775900904

Onnasch, L., Wickens, C. D., Li, H., & Manzey, D. (2014a). Human performance consequences of stages and levels of automation: an integrated meta-analysis. *Human Factors*, *56*(3). https://doi.org/10.1177/0018720813501549

Onnasch, L., Wickens, C. D., Li, H., & Manzey, D. (2014b). Human Performance Consequences of Stages and Levels of Automation. *Human Factors*, *56*(3), 476–488. https://doi.org/10.1177/0018720813501549

Parasuraman, R. (2000). Designing automation for human use: empirical studies and quantitative models. *Ergonomics*, *43*(7), 931–951. https://doi.org/10.1080/001401300409125

Parasuraman, R., & Christopher, D. (2008). Humans: Still Vital After All These Years of Automation. *Human Factors*, *50*(3), 511–520. https://doi.org/10.1518/001872008X312198.

Parasuraman, R., & Riley, V. (1997). Humans and automation: use, misuse, disuse, abuse. *Human Factors*, *39*(2), 230–253. https://doi.org/10.1518/001872097778543886

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *30*(3), 286–297. https://doi.org/10.1109/3468.844354

Porfirio, D., Saupp, A., Albarghouthi, A., & Mutlu, B. (2019). Computational Tools for Human-Robot Interaction Design. *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, 733–735.

Portugal, D., Alvito, P., Christodoulou, E., Samaras, G., & Dias, J. (2019). A Study on the Deployment of a Service Robot in an Elderly Care Center. *International Journal of Social Robotics*, *11*(2), 317–341. https://doi.org/10.1007/s12369-018-0492-5

Ratchford, M., & Barnhart, M. (2012). Development and validation of the technology adoption propensity (TAP) index. *Journal of Business Research*, *65*(8), 1209–1215. https://doi.org/10.1016/j.jbusres.2011.07.001

Rehrl, T., Troncy, R., Bley, A., Ihsen, S., Scheibl, K., Glende, S., Goetze, S., Kessler, J., Hintermueller, C., & Wallhoff, F. (2012). The Ambient Adaptable Living Assistant is Meeting its Users. *Proceedings of the AAL Forum 2012*, 629–636. https://doi.org/10.1.1.364.3969

Robins, B., Dautenhahn, K., Nehaniv, C. L., Mirza, N. A., François, D., & Olsson, L. (2005). Sustaining interaction dynamics and engagement in dyadic child-robot interaction kinesics: Lessons learnt from an exploratory study. *Proceedings - IEEE International Workshop on Robot and Human Interactive Communication*, *2005*, 716–722. https://doi.org/10.1109/ROMAN.2005.1513864

Rossi, S., Staffa, M., & Tamburro, A. (2018). Socially Assistive Robot for Providing Recommendations: Comparing a Humanoid Robot with a Mobile Application. *International Journal of Social Robotics*, *10*(2), 265–278. https://doi.org/10.1007/s12369-018-0469-4

Šabanovic, S., Bennett, C. C., Chang, W. L., & Huber, L. (2013). PARO robot affects diverse interaction modalities in group sensory therapy for older adults with dementia. *IEEE International Conference on Rehabilitation Robotics*. https://doi.org/10.1109/ICORR.2013.6650427

Sabelli, A. M., Kanda, T., & Hagita, N. (2011). A conversational robot in an elderly care center. *Proceedings of the 6th International Conference on Human-Robot Interaction - HRI '11*, 37. https://doi.org/10.1145/1957656.1957669

Sands, L. P., Albert, S. M., & Suitor, J. J. (2020). Understanding and Addressing Older Adults' Needs During COVID-19. *Innovation in Aging*, *4*(3), 1–3. https://doi.org/10.1093/geroni/igaa019

Schaefer, K. (2013). The Perception And Measurement Of Human-robot Trust. *Electronic Theses and Dissertations, 2004-2019*. https://stars.library.ucf.edu/etd/2688

Sheridan, T. B. (1992). Telerobotics, Automation, and Human Supervisory Control. In *MIT Press, Cambridge, MA*. https://doi.org/10.1109/MTAS.1993.232279

Shibata, T., Wada, K., Ikeda, Y., & Sabanovic, S. (2009). Cross-cultural studies on subjective evaluation of a seal robot. *Advanced Robotics*, *23*(4), 443–458. https://doi.org/10.1163/156855309X408826

Smarr, C. A., Mitzner, T. L., Beer, J. M., Prakash, A., Chen, T. L., Kemp, C. C., & Rogers, W. A. (2014). Domestic Robots for Older Adults: Attitudes, Preferences, and Potential. *International Journal of Social Robotics*, *6*(2), 229–247. https://doi.org/10.1007/s12369-013-0220-0

Smarr, C. A., Prakash, A., Beer, J. M., Mitzner, T. L., Kemp, C. C., & Rogers, W. A. (2012). Older adults' preferences for and acceptance of robot assistance for everyday living tasks. *Proceedings of the Human Factors and Ergonomics Society*, 153–157. https://doi.org/10.1177/1071181312561009

Soltan, K. (2019). *"They're coming to kill us": The role of science-fiction in shaping our attitude and the public discourse on an imagined future with humanoid robots/AI*. https://researchspace.auckland.ac.nz/handle/2292/47273

Soyama, R., Ishii, S., & Fukase, A. (2004). Selectable Operating Interfaces of the Meal-Assistance Device "My Spoon." *Advances in Rehabilitation Robotics*, 155–163. https://doi.org/10.1007/10946978_8

Stone, R. (2021). Developing a quality home care workforce to complement family caregivers and bridge the emerging care gap. In *Bridging the Family Care Gap* (pp. 321–340). Elsevier. https://doi.org/10.1016/b978-0-12-813898-4.00010-5

Svendsen, G. B., Johnsen, J. A. K., Almås-Sørensen, L., & Vittersø, J. (2013). Personality and technology acceptance: the influence of personality factors on the core constructs of the Technology Acceptance Model. *Behaviour and Information Technology*. https://doi.org/10.1080/0144929X.2011.553740

Syrdal, D. S., Dautenhahn, K., Koay, K. L., & Walters, M. L. (2009). The Negative Attitudes Towards Robots Scale and reactions to robot behaviour in a live Human-Robot Interaction study. *Adaptive and Emergent Behaviour and Complex Systems - Proceedings of the 23rd Convention of the Society for the Study of Artificial Intelligence and Simulation of Behaviour, AISB 2009*, *June 2014*, 109–115.

Tang, D., Yusuf, B., Botzheim, J., Kubota, N., & Chan, C. S. (2015). A novel multimodal communication framework using robot partner for aging population. *Expert Systems with Applications*, *42*(9), 4540–4555. https://doi.org/10.1016/j.eswa.2015.01.016

Taylor, R. M. (2017). Situational Awareness Rating Technique (Sart): The Development of a Tool for Aircrew Systems Design. In *Situational Awareness* (pp. 111–128). Routledge. https://doi.org/10.4324/9781315087924-8

Theodorou, A., Wortham, R. H., Bryson, J. J., Wortham, R. H., & Bryson, J. J. (2017). Designing and implementing transparency for real time inspection of autonomous robots inspection of autonomous robots. *Connection Science*, *29*(3), 230–241. https://doi.org/10.1080/09540091.2017.1310182
United Nations. (2020). World population ageing 2020. In *United Nations, Department of Economic and Social Affairs, Population Division* . Population Division, Department of Economic and Social Affairs. http://link.springer.com/chapter/10.1007/978-94-007-5204-7_6
Vicente, K. J., & Rasmussen, J. (1992). Ecological interface design: Theoretical foundations. *IEEE Transactions on Systems, Man, and Cybernetics*, *22*(4), 589–606. https://doi.org/10.1109/21.156574
Wachs, J., Stern, H., Edan, Y., Gillam, M., Feied, C., Smith, M., & Handler, J. (2007). Gestix: A doctor-computer sterile gesture interface for dynamic environments. *Advances in Soft Computing*, *39*, 30–39. https://doi.org/10.1007/978-3-540-70706-6_3
Wang, W., Chen, Y., Li, R., & Jia, Y. (2019). Learning and Comfort in Human-Robot Interaction: A Review. *MDPI Applied Sciences*, *9*(23). https://doi.org/10.3390/app9235152
Wickens, C. D., Li, H., Santamaria, A., Sebok, A., & Sarter, N. B. (2010). Stages and Levels of Automation: An Integrated Meta-analysis. *Human Factors*, *4*, 389–393.
Woo, J., Wada, K., & Kubota, N. (2012). Robot Partner System for Elderly People Care by Using Sensor Network. *4th IEEE RAS \& EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, 1329–1334.
Wortham, R. H. (2020). Transparency for Robots and Autonomous Systems: fundamentals, technologies and applications. In *Transparency for Robots and Autonomous Systems: Fundamentals, technologies and applications*. Institution of Engineering and Technology. https://doi.org/10.1049/pbce130e
Wortham, R. H., Theodorou, A., Wortham, R. H., & Theodorou, A. (2017). Robot transparency , trust and utility Robot transparency , trust and utility. *Connection Science*, *29*(3), 242--248. https://doi.org/10.1080/09540091.2017.1313816
Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, *67*, 221–232. https://doi.org/10.1016/j.chb.2016.10.028
Wylie, G., & Allport, A. (2000). Task switching and the measurement of “switch costs.” *Psychological Research*, *63*(3–4), 212–233. https://doi.org/10.1007/s004269900003
Xu, A., & Dudek, G. (2016). Towards modeling real-time trust in asymmetric human–robot collaborations. *Springer Tracts in Advanced Robotics*, *114*, 113–129. https://doi.org/10.1007/978-3-319-28872-7_7
Ye, J., Huang, J., He, J., Tao, C., & Wang, X. (2012). Development of a width-changeable intelligent walking-aid robot. *2012 International Symposium on Micro-NanoMechatronics and Human Science, MHS 2012*, 358–363. https://doi.org/10.1109/MHS.2012.6492438
Zafrani, O., & Nimrod, G. (2019). Towards a holistic approach to studying human–robot interaction in later life. *The Gerontologist*, *59*(1), e26–e36. https://doi.org/10.1093/geront/gny077

Appendices

A. Ethical approval

Human Subjects Research Committee

אוניברסיטת בן-גוריון בנגב
Ben-Gurion University of the Negev

10.12.2015

To: Prof Tal Oron-Gilad, Department Industrial Engineering and Management

From: Prof. Yoella Bereby-Meyer, Chairperson, Human Subjects Research Committee of Ben-Gurion University
Re.: Application for ethics approval for research project
Request Sub-Number: 1315

Research Title:
Human-Robot Interaction

Decision of the Committee: Granted

Note: The decision of this committee pertains only to ethical considerations involved in the conduct of the research

Prof. Yoella Bereby-Meyer
Chairman of the Human Subject Research Committee

P.O.B 653, Beer Sheva 84105, Israel | ת.ד 653 באר שבע 84105 | קריה על-שם משפחת מרקוס
http://web2.bgu.ac.il/ethics2 | E-mail: hsrCommittee@bgu.ac.il | Marcus Family Campus

B. General explanation for the experiment

<u>Human-Robot Interaction study</u>

The current experiment will take place in Ben-Gurion University and will study the interaction between humans and robots and will study the interaction between humans and robots.

During the experiment you will be asked to perform a few tasks related to the robot. In some of the tasks, the robot's or the environment's parameters will be changed. In case you are asked to interact with the robot, please do so naturally. The robot has a safety mechanism so that it does not collide with you or harm you in any way.

The identifying details of the participants are not saved. Each participant receives a unique number which is separated from the participant's personal details and all the questionnaires filled out will be handed over to the lead investigator in charge of the research and will be saved.

If for any reason you feel uncomfortable, please stop the experiment and the experimenter will approach you immediately. At any time and at any stage you can, if you wish, discontinue your participation in the research. If you want the experiment to stop, you will be released from the experiment.

If you wish to participate in this study with the robot, kindly fill in your name and contact details in the next page.

For additional details please contact:
Vardit Sarne-Fleischmann: sarne@post.bgu.ac.il
Prof. Tal Oron-Gilad: orontal@bgu.ac.il
Prof. Yael Edan: yael@bgu.ac.il

C. Consent Form

Consent Form

Dear Subject,

Please read the explanation for the experiment. If there are any questions, we will be happy to answer. During the experiment, you will be asked to give the robot directions to place objects in a certain arrangement. The experiment would be conducted in the intelligent robotics lab, Ben-Gurion University of the Negev. The experiment will last for 10 – 15 minutes.

It is important to note that the experiment is anonymous. The identification details of the subjects are not kept. Each participant receives a subject number that is separated from the examinee's specifications. All the questionnaires filled out will be handed over to the lead investigator who is in charge of the research and will retain its responsibility.

If for any reason you feel uncomfortable, please stop the experiment by raising your hand or by verbal request.

I, the undersigned*:

First name and surname:	ID:
Phone number:	Signature:

*This statement is confidential and cannot be transferred or used for any purpose except for the purpose of this research.

Date: ___________________

Experimenter's Signature:

Thank you for your participation in the research.

D. **Software of Robots (open source codes on GitHub):**

https://github.com/BGUPioneer/mobile-robot/tree/master/people_follower/src

https://github.com/users/samuelolatunji/projects/1

E. **Questionnaires**

Preliminary Questionnaire

*Required

Preliminary questionnaire

1. Number asterisked (to be completed by the researcher) * *

____

Preliminary questionnaire

2. Age *

____

3. Gender *

Mark only one oval.

- Male
- Famale

4. Education *

Mark only one oval.

- High School
- BA
- Master's degree
- Ph.D
- Other

5. Field of study

____

6. Have you had any prior experience taking care of an older adult?

Mark only one oval.

- Yes
- No
- Other: _______________

7. Do you have any experience with hazard perception in an older adult home?

Mark only one oval.

- Yes
- No
- Other: _______________

Skip to question 2

Technologies Used - please indicate how frequently you use/do each of the things below:

0- Never
1- Once every six months to a year
2- Once every two months to five months
3- Once in a month
4- 1 to 3 times a week
5- Almost every day

8. 1. Use a GPS system: *

Mark only one oval.

0	1	2	3	4	5

9. 2. Use “self check-out” at stores: *

Mark only one oval.

0	1	2	3	4	5

10. 3. Deposit over $100 at an ATM: *

Mark only one oval.

0	1	2	3	4	5

11. 4. Video calling such as Skype: *

Mark only one oval.

0	1	2	3	4	5

12. 5. Voice over IP calling:

Mark only one oval.

0	1	2	3	4	5
◯	◯	◯	◯	◯	◯

13. 6. Online data backup services: *

Mark only one oval.

0	1	2	3	4	5
◯	◯	◯	◯	◯	◯

14. 7. Buy an item at a vending machine or pay a parking meter using your cell phone: *

Mark only one oval.

0	1	2	3	4	5
◯	◯	◯	◯	◯	◯

Technology Adoption Propensity questionnaire (TAP) - Please indicate your agreement with the following statements:

1- Strongly disagree
2- Disagree
3- Neutral
4- Agree
5- Strongly agree

15. 1. Technology gives me more control over my daily life. *

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

16. 2. Technology helps me make necessary changes in my life. *

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

17. 3. Technology allows me to more easily do the things I want to do at times when I want to do them. *

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

18. 4. New technologies make my life easier. *

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

19. 5. I can figure out new high-tech products and services without help from others. *

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

20. 6. I seem to have fewer problems than other people in making technology work. *

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

21. 7. Other people come to me for advice on new technologies. *

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

22. 8. I enjoy figuring out how to use new technologies. *

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

23. 9. Technology controls my life more than I control technology. *

Mark only one oval.

1	2	3	4	5
⬭	⬭	⬭	⬭	⬭

24. 10. I feel like I am overly dependent on technology. *

Mark only one oval.

1	2	3	4	5
⬭	⬭	⬭	⬭	⬭

25. 11. The more I use a new technology, the more I become a slave to it. *

Mark only one oval.

1	2	3	4	5
⬭	⬭	⬭	⬭	⬭

26. 12. I must be careful when using technologies because criminals may use the technology to target me. *

Mark only one oval.

1	2	3	4	5
⬭	⬭	⬭	⬭	⬭

27. 13. New technology makes it too easy for companies and other people to invade my privacy. *

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

28. 14. I think high-tech companies convince us that we need things that we don't really need. *

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

Negative Attitude toward Robots Scale (NARS) Questionnaire

1- Strongly disagree
2- Disagree
3- Neutral
4- Agree
5- Strongly agree

Please indicate your agreement with the following statements

29. 1. I would feel uneasy if robots really had emotions. *

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

30. 2. Something bad might happen if robots developed into living beings *

Mark only one oval.

1	2	3	4	5
⬭	⬭	⬭	⬭	⬭

31. 3. I would feel relaxed talking with robots *

Mark only one oval.

1	2	3	4	5
⬭	⬭	⬭	⬭	⬭

32. 4. I would feel uneasy if I was given a job where I had to use robots *

Mark only one oval.

1	2	3	4	5
⬭	⬭	⬭	⬭	⬭

33. 5. If robots had emotions I would be able to make friends with them *

Mark only one oval.

1	2	3	4	5
⬭	⬭	⬭	⬭	⬭

34. 6. I feel comforted being with robots that have emotions *

Mark only one oval.

1	2	3	4	5
⬭	⬭	⬭	⬭	⬭

35. 7. The word “robot” means nothing to me *

Mark only one oval.

1	2	3	4	5
⬭	⬭	⬭	⬭	⬭

36. 8. I would feel nervous operating a robot in front of other people *

Mark only one oval.

1	2	3	4	5
⬭	⬭	⬭	⬭	⬭

37. 9. I would hate the idea that robots or artificial intelligences were making judgements about things. *

Mark only one oval.

1	2	3	4	5
⬭	⬭	⬭	⬭	⬭

38. 10. I would feel very nervous just standing in front of a robot *

Mark only one oval.

1	2	3	4	5

39. 11. I feel that if I depend on robots too much, something bad might happen. *

Mark only one oval.

1	2	3	4	5

40. 12. I would feel paranoid talking with a robot *

Mark only one oval.

1	2	3	4	5

41. 13. I am concerned that robots would be a bad influence on children *

Mark only one oval.

1	2	3	4	5

42. 14. I feel that in the future society will be dominated by robots *

Mark only one oval.

1	2	3	4	5
◯	◯	◯	◯	◯

Post-Task Experience

Please rate your experience while operating the robot with the following questions

1. Participant No.

2. Participant No.

3. Please select the task you just completed

Mark only one oval.

- ( ) 1
- ( ) 2

4. Please, also select the mode you just completed

Mark only one oval.

- ( ) Mode A
- ( ) Mode B

Assessment of Task load

Please rate your experience while carrying out the task

5. Mental Demand: How mentally demanding was the task?

Mark only one oval.

	1	2	3	4	5	
very low	◯	◯	◯	◯	◯	very high

6. Physical Demand: How physically demanding was the task?

Mark only one oval.

	1	2	3	4	5	
very low	◯	◯	◯	◯	◯	very high

7. Temporal Demand: How hurried or rushed was the pace of the task?

Mark only one oval.

	1	2	3	4	5	
very low	◯	◯	◯	◯	◯	very high

8. Performance: How successful were you in accomplishing what you were asked to do?

Mark only one oval.

	1	2	3	4	5	
perfect	◯	◯	◯	◯	◯	failure

9. Effort: How hard did you have to work to accomplish your level of performance?

Mark only one oval.

	1	2	3	4	5	
very low	⬭	⬭	⬭	⬭	⬭	very high

10. Frustration: How insecure, discouraged, irritated, stressed, and annoyed were you?

Mark only one oval.

	1	2	3	4	5	
very low	⬭	⬭	⬭	⬭	⬭	very high

System Usability

Please rate your experience while using the system

11. 1. I think that I would like to use this system frequently

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

12. 2. I found the system unnecessarily complex

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

13. 3. I thought the system was easy to use

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

14. 4. I think that I would need the support of a technical person to be able to use this system

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

15. 5. I found the various functions in this system were well-integrated

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

16. 6. I thought there was too much inconsistency in this system

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

17. 7. I would imagine that most people would learn to use this system very quickly

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

18. 8. I found the system very cumbersome to use

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

19. 9. I felt very confident using the system

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

20. 10. I needed to learn a lot of things before I could get going with this system

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

Situation Awareness Rating

Please rate your awareness of the situation in the task with the following questions

21. 1. Complexity of Interaction: Is it complex with many interrelated components (High) or is it simple and straightforward (Low)?

Mark only one oval.

	1	2	3	4	5	6	7	
very low	⬭	⬭	⬭	⬭	⬭	⬭	⬭	very high

22. 2. Concentration of Attention: Are you concentrating on many aspects of the interaction (High) or focused on only one (Low)?

Mark only one oval.

	1	2	3	4	5	6	7	
very low	⬭	⬭	⬭	⬭	⬭	⬭	⬭	very high

23. 3. Information Quantity: How much information have you gained about the environment the robot was navigating in? Have you received and understood a great deal of knowledge (High) or very little (Low)

Mark only one oval.

	1	2	3	4	5	6	7	
very low	⬭	⬭	⬭	⬭	⬭	⬭	⬭	very high

4/14/2021 Final Questionnaire

Final Questionnaire

Please assess your overall experience with the system and task

1. Participant No.

____

2. Overall, this task was?

Mark only one oval.

	1	2	3	4	5	6	7	
Very Difficult	◯	◯	◯	◯	◯	◯	◯	Very Easy

3. If you found the task difficult or worse, can you please describe briefly why?

____

4. In future, what would you like the system to include to make the task easier for you?

____

https://docs.google.com/forms/d/1PzpgBZGUQUOThiuwYLWMwMkMwsK0ipyJfQZVTHdAA3I/edit 1/2

F. Raw data and results of data analyses:

https://github.com/samuelolatunji/data_esr10_socrates

תקציר

צמיחה המהירה באוכלוסייה העולמית של מבוגרים ללא עליה תואמת במטפלים ואנשי מקצוע בתחום הבריאות צפויה להפוך לאתגר חברתי מרכזי. השימוש ברובוטים מסייעים (ARs) יכול לגשר על פער זה של טיפול בקשישים על ידי סיוע לאלו המבוגרים יותר בפעילויות החיים היומיומיות. הצגת AR לאוכלוסייה זו כוללת אתגרי אינטראקציה מובנים. תזה זו עוסקת באתגרים אלה עם ARs בשלושה שלבים :

שלב א. גישור על פער שקיפות האוטומציה ב ARs -לטיפול בקשישים: תשומת לב לכך ששקיפות המספקת שאינה מוחצת, אך עדיין מספקת מידע מספיק למשתמשים להשלמת המשימות. הוגדרו ויושמו רמות שקיפות, שהוגדרו כמידת המידע שנמסר למשתמש.

שלב ב. שמירה על אוטונומיה באינטראקציה עם הAR : מתן עדפיות לעדפות שלבי הסתגלות על ידי שמירה על רמה מסוימת של אוטונומיה מבלי להקטין את הסיוע הרובוטי. רמות האוטומציה, המוגדרות כמידת ביצוע מסימות על ידי הרובוט, פותחו ויושמו על ידי הגדרת הקצאות פונקציות.

שלב ג. שילוב של שקיפות ואוטונומיה לשיפור המעורבות: שיתוף משתמשים למניעת שעמום, השתקעות בישיבה או אובדן כישורים עקב חוסר פעילות ממושכת תוך מתן מידע מספיק לביצוע משימות שלא יציפו או יבלבלו אותם. תוכננה מסגרת המשלבת את מודלי LoT ו LOA - כדי להגדיר את מידת הסיוע שהרובוט אמור לספק לצורך מעורבות עם משוב הולם כדי להבטיח שהמשתמש יישאר בתהליכים ללא עומס יתר של מידע.
שלב שלישי זה של המחקר שילב את התובנות של שני השלבים הראשוניים כדי לייצר מודל עיצוב אינטראקציה המוערך באופן אמפירי עם הנחיות להתפתחויות והערכות נוספות ב ARs -אחרים לטיפול בסיעוד לקשישים.

סיכום: התזה מקדמת את עיצוב האינטראקציה על ידי ARs לטיפול בקשישים, ומתמקדת באתגרים העיקריים באינטראקציה. מודלים LoT ו LOA -ואינטגרציה של LoT-LOA שפותחו והוערכו מצביעים על כדאיות התכנון ועל פוטנציאל ההטמעה ב ARs -אחרים לטיפול בסיעוד עבור קשישים.

העבודה נעשתה בהנחיית

פרופ' יעל אידן

פרופ' טל אורון-גלעד

מהמחלקה להנדסת תעשייה וניהול

בפקולטה להנדסה

אוניברסיטת בן-גוריון בנגב

רובוטים מסייעים לגיל השלישי:

תיכון האינטראקציה לרמות משתנות של אוטומציה

מחקר לשם מילוי חלקי של הדרישות לקבלת תואר "דוקטור לפילוסופיה"

מאת

סמואל אולטונג'י

הוגש לסינאט אוניברסיטת בן-גוריון בנגב

Tal Oron-Gilad Yael Edan

אישור המנחים ________________________________

אישור דיקן בית הספר ללימודי מחקר מתקדמים ע"ש קרייטמן ________________

כט' ניסן תשפ"א **14 אפריל 2021**

באר שבע

רובוטים מסייעים לגיל השלישי:

תיכון האינטראקציה לרמות משתנות של אוטומציה

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מאת

סמואל אולטונג'י

הוגש לסינאט אוניברסיטת בן-גוריון בנגב

כט' ניסן תשפ"א | **14 אפריל 2021**