BEN-GURION UNIVERSITY OF THE NEGEV

FACULTY OF ENGINEERING SCIENCES

DEPARTMENT OF INDUSTRIAL ENGINEERING AND MANAGEMENT

Levels of automation in a robot assistant for elder care

THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE M.Sc. DEGREE

By: Dana Gutman

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Abstract

This thesis examined the interaction between assistive robots and humans, focusing on levels of automation (LOA). We focused on assistive robots in daily activities for older adults with adequate consideration for their expectations and preferences. The aim is for the robot to perform tasks in a collaborative manner to keep the older adults as active as possible in the interaction while preserving their independence. The task becomes a joint task between the older adult and the robot.

LOA refers to the degree of robot autonomy included in a given task. Creating a successful interaction is a challenging task. To avoid idleness, sedentariness, boredom, or loss of skill in the long run, the balance between assisting the user as much as possible and involving them in the task must be maintained,. This study revisits the study of automation levels in everyday tasks such as table editing, specific to the adult population. We evaluated several different aspects that influence the interaction in combination with LOA. Specifically, the research focused on assessing the influence of transparency, feedback types, workload, and complexity in combination with LOA on different interaction and performance aspects.

Two experimental systems were specially developed and evaluated in three experiments with older adults and simulated caregivers. The first part of the research examined robot assistance to the elderly population in a home environment. This preliminary experiment served as a case study to explore different influencing factors with fourteen older participants (8 Females and 6 Males, aged 62-86, M=69.8, SD=4.48). A collaborative robot was programmed in a table-setting task performed jointly by an older adult and the robot with two levels of automation (LOA) and two levels of transparency (LOT) conditions. This study explored how LOA and LOT influences the quality of interaction (QoI). The QoI is a construct that entails the fluency, understanding, engagement and comfortability during the interaction. Results revealed that at the high LOA higher performance was consistently obtained. Furthermore, at the low LOT it was recommended to avoid clutter and confusion among the participants. The second part of the research used the same system as in the case study experiment and examined the effect of LOA and different feedback modalities in a table clearing robot assistant for elder care. 21 older adults (8 females and 13 males aged 70-86, M=74, SD=4.12) participated in the study. Two different feedback modalities (visual and auditory) were evaluated for three different LOA. The visual feedback included the use of LEDs and a GUI screen. The auditory feedback included voice recordings. Results provided insight into older adult's preferences; they would prefer the voice recording feedback. Most of the older adults testified that they would like a similar robot in their home to assist them, emphasizing the relevance of the developed system.

In the third part, the examination of LOA modalities was tested in a task that was designed to include different levels of task complexity and workload. The goal was to perform the experiment with and for adults but due to the Covid-19 pandemic we were unable to recruit adults for the experiment and therefore focused on simulated caregivers instead. The effect of LOA, task complexity and task workload on the quality of the interaction was examined in a joint human-robot assembly task. Eighty students from BGU (46 females and 36 males, aged 24-29, M=26, SD=1.4) were recruited as participants. This research investigated two levels of automation, two levels of workload (LOW) and two levels of complexity (LOC) in an assembly task using a robotic arm equipped with a suction gripper. The quality of interaction was measured in terms of objective and subjective measures including effectiveness, efficiency, understanding, and perceived workload. The results revealed that LOW had a significant impact on most of the measures of interaction quality and that it is an important component in designing a joint task between human and robot.

A conclusion that emerged from the first and second parts of the research refers to the impact of the different LOA on the quality of interaction. Results revealed that in general, the adult population will be pleased to use an assistive robot that will help them with daily tasks. The best configuration for them is when the assistance is combined with their participation in the task. An aspect that can add to this and improve the interaction is by incorporating feedback from the robot during the task; this increases the adult involvement. As well, a certain level of transparency during the task makes the adult feel aware what is happening and makes him/her feel better leading to improved quality of interaction. In performing a joint task with a robot in parallel with additional tasks, participants prefer a higher level of automation that will allow them to distribute their attention more efficiently. The task complexity did not influence performance; however, this aspect should be examined in depth in future studies in different tasks and with different populations.

Keywords: social assistive robots, assistive robots, levels of automation, levels of workload, levels of complexity, HRI, feedback, older adults.

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This thesis was performed in parallel to the thesis of Noa Markfeld (Markfeld, 2021) which focused on *Feedback Design for Older Adults*. Some of the development work on the Kuka and experiments were performed in collaboration. Noa focused on the feedback design while I focused on the levels of automation.

This work has been reviewed and presented at:

C1. Olatunji, S., N. Markfeld, **D. Gutman**, S. Givati, V. Sarne-Fleischmann, T. Oron-Gilad, Y. Edan. 2019. *Proceedings of the International Conference on Social Robotics* (pp 568-577), 11876 LNAI Lecture Notes in Computer Science. Improving the Interaction of Older Adults with a Socially Assistive Table Setting Robot. Springer International Publishing http://dx.doi.org/10.1007/978-3-030-35888-4_53.

C2. 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. In *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. Extended abstract.

C3. **Gutman, D.**, N. Markfeld, S. Olatunji, V. Sarne-Fleischmann, T. Oron-Gilad, Y. Edan. 2019. Evaluating fluency in robot-assisted table setting for older adults, ICR 2019 – 6th Israeli Conference of Robotics, July 2019, Herzelia, Israel. Abstract, oral presentation.

Submitted/in preparation journal publications

J1. **Gutman, D.**, S. Olatunji, N. Markfeld, S. Givati, V. Sarne-Fleischmann, T. Oron-Gilad, Y. Edan. 2020a. Evaluating levels of automation and feedback in an assistive robotic table clearing task for eldercare. In preparation for MDPI Applied Sciences.

J2. **Gutman D.**, S. Olatunji, Y. Edan. 2020b. Levels of automation for different levels of workload and task complexities in human-robot collaboration. October 2020.

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 (submitted, minor revision in process).

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Chapter 1. Introduction

1.1 Overview

The aging population rate is rising rapidly (United Nations, 2017) while the number of caregivers and nurses is deteriorating (Buerhaus et al. 2012). The high cost of long-term care for older adults is an issue that cannot be ignored, and it increases the financial burden on public health service and family members (Aurilla et al. 2011). A promising solution to help overcome this financial burden along with the lack of caregivers is the development of assistive robots (Broekens et al. 2009; Shishehgar et al. 2019). It is important that the robots should augment the quality of life for the older adults yet not take away what they enjoy about life (Lewis et al. 2016).

This research focuses on the interaction between assistive robots and older adults. This study revisits the study of automation levels in everyday tasks such as table editing, specific to the adult population. The research initially aimed to focus only on older adults. However, with the outbreak of COVID-19 it was impossible to complete experiments with older adults. The first part of the research included two experiments and focused on user studies with older adults. The last experiment was conducted with students that simulated caregivers and serves as a preliminary experiment to be followed up in a similar manner with older adults in the future.

1.2 Background and problem description

<u>Assistive robots</u>

Assistive robots are generally designed to give aid or support to a human user (Kulyukin 2006; Pfeil-Seifer et al. 2005). Excellence in patient care can be achieved by using assistive robots (Nejat et al., 2009) in activities of daily living (ADL) and instrumental activities of daily living (IADL). ADLs include tasks essential to maintain older adults independence, such as toileting, eating, or bathing (Mucchiani et al. 2017). IADLs are tasks such as using a telephone, cooking, doing laundry or using transportation (Smarr et al. 2014). While there has been some progress in the design and development of assistive robots to aid in elder care (Kachouie et al. 2014), many challenges remain and call for further research. These challenges include among others misinterpretation of robot roles by older people, mismatch of expectations, insufficient engagement of the older adult while interacting with the robot, robot acceptance by the older adult, and ethical implications of using robots for elder care (Frennert et al. 2014)

<u>Levels of automation (LOA)</u>

Autonomous capabilities are being developed for a wide range of systems in order to reduce labor, extend human capabilities, and improve human safety (Endsley 2017a). Automation does not have to exist in an all-or-none fashion and can vary by level (Endsley 2017a; Vagia et al. 2016). The levels can vary in degree of control, responsibility and decision making of the human and system (Chidester et al. 1991). The lowest level usually has minimum system involvement and the user control the robot. This involvement increases through the levels up to the highest degree, where the system is fully in charge of the task as seen in the initial LOA taxonomies proposed by Sheridan (Sheridan et al. 1978).

LOA can be defined as the degree to which automation is employed in a given task (Endsley et al. 1999). In terms of HRI, it is described as the extent to which the robot is given autonomy to perform a particular task (Parasuraman et al. 2008). The goal of LOA is to find the degree that maximizes the efficiency, effectiveness and performance of the human interacting with the robot. The extent of the robot's autonomy has been defined in literature by various authors at different levels and with various taxonomies on a scale from fully autonomous to fully manual (Vagia et al. 2016). Designing LOA to fit the demands of the older adults in SAR operations is an important element of the interaction (Vagia er al. 2016). In order for such robots to be operated efficiently and effectively by older adults and non-technological users, it is important to examine if and how increasing the robotic system's LOA impacts their performance (Olatunji et al. 2020).

Robot feedback

Incorporating feedback in human-robot-interaction improves the interaction (Mohammad et al. 2007). Successful interaction requires communication between the human and the robot which generally involves sending and receiving of information to achieve specific goals (Doran et al.2017). Existing studies reveal that the information presented to the user significantly influences his / her comprehension of the robot's behavior, performance, and limitations of the robot (Pangaro 2009), influencing interaction quality (Zafrani et al. 2019a). A robot that provides feedback is more likely to be perceived as a social communication partner (Heerink et al. 2009). Additionally, users that did not receive feedback during the interaction stated that they would like to receive feedback from the robot.

Feedback provided to the users could be in different forms which could be varied with regards to mode, timing and other dimensions of the feedback (Avioz-Sarig et al. 2020). Visual feedback is one of the most popular feedback modalities since it is considered a natural communication channel (Perrin et al., 2008).The most common is using a screen to display information (Nicole Mirnig et al. 2014) and the use of lights (Baraka et al. 2018). Auditory feedback concerns the use of sound to communicate information to the user about the state of the robot (Rosati et al. 2013).

Levels of transparency (LOT)

Transparency is the degree of task-related information provided by the robot to the older adults to keep them aware of its state, actions and intentions of the robot (Chen et al. 2018). The information presented by the robot should conform with the perceptual and cognitive peculiarities of the older adults (Feingold Polak et al. 2018; Fisk et al. 2009; Smarr et al. 2014) and relate to the environment, task, and robot (Lyons 2013). Too little information may not be sufficient to ensure reliable interaction with the robot (Launay et al. 2014), whereas too much information could cause confusion and error (Lyons 2013).

Levels of workload (LOW)

It is a common belief that heavy workloads lead to elevated stress and reduced efficiency meaning workload effects performance (Glaser et al. 1999). Performance on a secondary task has been suggested as a useful method for assessing the attentional load placed on a performer (Ellmers et al. 2016; de Jong 2010). It is important to devise the secondary tasks so that it adds load. The effect of adding too much contextual information could increase extraneous load in less-skilled performers in a similar fashion to an unrelated secondary task (Runswick et al. 2018). Adding cognitive load during a vehicle-driving task revealed negative effect on processes under conscious control and could potentially have a positive effect on more automatic processes (Runswick et al. 2018). The use of a secondary task could induce the prioritization of more relevant information sources in working memory and force the performer to ignore un-relevant sources in order to avoid overloading resources.

Levels of complexity (LOC)

Task complexity has been identified in previous research as a critical factor influencing the LOA design in human robot interaction (Beer et al. 2014) and impacting performance (Crandall et al. 2002). The complexity level depends on several factors such as the number and type of subtasks that must be managed individually, sequentially or simultaneously, the level of difficulty and/or criticality of each of these subtasks, the time required to complete subtasks, the degree of human intervention required for each of these subtasks, and the amount of clutter in an environment (Burke et al. 2004; Ginoian 1976; Kristoffersson et al. 2013). There are limited studies that have considered the task complexity in the design and evaluation of LOA particularly in the case of care for older adults. Performance on a task depends not only on objective complexity (a task characteristic) but also on one's perception of the task complexity (Chen et al. 2014).

1.3 Research objectives

The objective of this research was to evaluate the influence of LOA in human robot interaction for older adults. Two systems were designed and developed for different tasks. The specific objectives were to:

1. Design the different levels of automation of the different tasks.
2. Assess the influence of LOA on user's interaction.
3. Identify the influence of transparency (LOT), feedback types, workload (LOT) and task complexity (LOC) in combination with LOA on user's interaction.

1.4 Thesis structure

The overall research methodology is depicted in chapter 2. The research includes three separate parts corresponding to three experiments that evaluate influence of mainly LOA in combination with LOT (study 1, chapter 3), feedback (study 2, chapter 4), LOW and LOC (study 3, chapter 5) on the interaction. Each chapter is an independent publication and as such includes a focused literature review and details the experimental and analysis methods and results. Overall conclusions and future research are discussed in chapter 6.

Chapter 2. Methodology

2.1 Overview

This research aims to evaluate the influence of LOA along with different parameters on the interaction of older adults interacting with assistive robots. Due to limited access to older adults due to the COVID-19 pandemic, one of the studies was not performed with older adults. Three experiments were designed to evaluate influence of LOA on user's quality of interaction (QoI); each study focused on a different influencing parameter combined with LOA. In the first study, we examined the influence of LOA and LOT on QoI between the older adults and a robot. The second study examined the influence of LOA with types of feedback on the QoI between the older adults and a robot. In the third study, a combination of different LOAs with LOW and LOC was examined with simulated caregivers. The studies were performed in a series with conclusions from each study used as inputs in the next study.

Table 1. Experimental design

	Study 1	Study 2	Study 3
Independent variable	LOA	LOA	LOA
	Levels of transparency (LOT)	Feedback	Levels of workload (LOW)
			Levels of complexity (LOC)
Robot platform	KUKA	KUKA	DOBOT
Task	Table setting	Table clearing	Cubes assembling
Population	Older adults	Older adults	Students (In light of the circumstances of COVID-19)
Thesis chapter	Three	Four	Five
Reference	C1, C3, J3	J1	J2

2.2 Study 1: Influence of LOA & LOT on the QoI

This study explored how LOA and LOT influences the quality of interaction (QoI). Details are provided in Chapter 3. This exploratory work was conducted in collaboration with Markfeld, 2020 and appears in publications C1, C3 and J3.

In order for such robots to be operated efficiently and effectively by older adults, it is important to examine if and how increasing the robotic system's level of automation (LOA) impacts their performance (Beer et al. 2014). To ensure transparency of the robot's role at all times, the LOA implementation is reflected in the ways through which the users interact with the robots. Transparency in this context is the degree of task-related information provided by the robot to the older adults to keep them aware of its state, actions and intentions of the robot (Chen et al. 2018). It is essential that the level of transparency (LOT) of the information being presented to the older adults conforms with their perceptual and cognitive peculiarities such as the processing and interpretation of the information provided by the robot (Feingold Polak et al. 2018; Smarr et al. 2014).

A KUKA LBR iiwa 14 R820, 7 degrees of freedom collaborative robotic arm equipped with a pneumatic gripper was programmed in a table-setting task performed jointly by an older adult and the robot with two LOA and LOT conditions.

Two LOA conditions were designed as follows:

> *Low LOA condition*. 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 condition*. The robot assists 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.

The two conditions differed by the purpose of the information provided by the robot; LOT conditions were set as follows:

> *Low LOT condition.* The low level of information included text messages that specified the status of the robot by indicating **what** it was doing (e.g. bringing a plate, putting a fork)
>
> *High LOT condition.* The high level of information included also the **reason** for this status (i.e. I'm bringing the plate since you asked me).

During the experiment, many participants noted the fact that the interaction with the robot is purely visual interferes with them, and the use of voice may improve the interaction. This point led us to the next study - where we focused on how feedback modalities affect the collaboration between the adult and the robot.

Based on the conclusions from this experiment, and given the nature of the population, it was decided to set the LOA at the high level where consistently higher performance was obtained. Accordingly, the LOT is set at the low level in order to avoid clutter and confusion among the participants.

2.3 Study 2: Influence of LOA & feedback on the QoI

In this second part, we continued to examine robotic assistance to the elderly population in the home environment. For this purpose, we used the *same system* as in the first study experiment, while adding changes and upgrades depending on the feedback modalities employed. Adding the feedback was in addition to implementing three levels of automation in a table clearing task. The reason three automation levels were applied in this experiment, compared to two in the previous experiment is that we saw that most adults in the previous experiment preferred the higher level of automation. We wanted to examine this time what will happen when we insert a level that is in between the 2 levels that have been applied. This is because our goal is to examine what is the best level for adults in this task. Details are provided in Chapter 4 and in publication J1.

The correct choice of interfaces between the assisting environment and the user is of high importance (Broekenset al. 2009). Older adults' interaction with robots requires effective feedback to keep them aware of the state of the interaction for optimum interaction quality (Beer, Fisk, and Rogers 2014). The feedback is the information provided by the robot. The types of feedback were designed as follows:

Visual:

- *GUI screen* was presented on a PC screen, located on a desk to the left of the user.
- LED lights were embedded in the robot and connected to the system using a Raspberry Pi computer.

Audio:

- Voice recordings was transmitted to the user through a speaker system connected to the main computer.

The experimental results provide insight into a daily task of clearing a table that older adults would prefer a robot to assist with. Most of the older adults testified that they would like a similar robot in their home to assist them, emphasizing the relevance of the developed system.

2.4 Study 3: Influence of LOA & LOW & LOC on the QoI

The examination of LOA modalities on adults' daily environment was continued, while changing the robotic platform and the examined task. Originally, another robotic arm, DOBOT magician was programmed to assist the adult in routine tasks. The task chosen to implement this was to assemble a desired configuration of cubes of different colors, where the robot will help them bring the cubes to the user one after the other. In addition, the task was examined at different levels of workload (LOW), and at different levels of complexity (LOC).

The experiment was performed on a student population simulating caregivers. Details are provided in Chapter 5 and in publication J2.

The experimental design includes three independent variables: LOA (two levels), LOW (two levels) and LOC (two levels). A between-within participants experimental design was conducted with the LOA as the within variables while LOW and LOC were the between variables.

In this experiment, as mentioned we went back to implementing two levels of automation. This is in light of the fact that in this experiment unlike the others there are three independent variables (rather than two) and therefore this makes the experiment more complicated. Therefore and in light of the limitations of the experiment we decided that it would be more correct to implement two levels of automation.

LOA conditions:

- *Low LOA* - The human operator (user) has the autonomy over the type and order of cubes desired. The human operator must identify the type of block needed to fit the required configuration to be assembled per time and then select the required cube through the user interface. The robot supports the user by bringing the type of cube the user selected.
- *High LOA* - The robot has the autonomy to bring the specific type of cube and in the order preprogrammed in its operation. The user does not have to identify a specific type of cube. S/he simply demands for a cube through the user interface and the robot brings the type of cube suitable for the specific configuration assembled per time.

LOW conditions:

- *Low LOW* - The users perform only the main task that consists of assembling cubes to match the specific configuration required per time. The workload involves several task demands such as the physical demand of arranging the cubes, mental demand of thinking about the type of cube that would match the required configuration and some temporal demand related to completing the task in the shortest possible time.
- *High LOW* - The users carry out the main task (composed of the aforementioned dimensions of workload) along with a secondary task. The secondary task was an off-the shelf well known cognitive game, the "RUSH HOUR" thinking game. It involves arranging toy cars in a way to get a specific car out of a gridlock. There are tabs at each stage showing how to arrange the cars, and afterwards, the player has to find a way to get the required car out. Once the user has managed to get the red car out, he/she advances a stage and arranges the cars according to what appears on the tab of the next stage. This contributes additional task demands to the overall workload.

LOC conditions:

- *Low LOC* - the cubes for the assembly differ only by color. The users are required to assemble the cubes to match particular configurations characterized by differences in color pattern. The complexity involves a partial dimension of component complexity where a specific number of cubes must be used to assemble the required configuration and coordination complexity where sequence and location of the specific color of cubes must be considered.
- *High LOC* - the cubes for the assembly differ in color and by the numbers on a particular side. The users are required to assemble the cubes in color patterns as done in the low LOC condition, but in addition, they must ensure that the specific numbers on specific color's of cubes match the required configuration per time. This therefore includes the

low LOC dimensions of complexity with an additional information cue (presence of numbers) along with a spatial consideration (position of the number in the configuration).

Chapter 3. Influence of LOA and LOT on QoI

Improving the Interaction of Older Adults with a Socially Assistive Table Setting Robot

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Abstract. This study provides user-studies aimed at exploring factors influencing the interaction between older adults and a robotic table setting assistant. The influence of level of automation (LOA) and level of transparency (LOT) on the quality of the interaction was considered. Results revealed that the interaction effect of LOA and LOT significantly influenced the interaction. A lower LOA which required the user to control some of the actions of the robot influenced the older adults to participate more in the interaction when the LOT was low compared to situations with higher LOT (more information) and higher LOA (more robot autonomy). Even though, the higher LOA influenced more fluency in the interaction, the lower LOA encouraged a more collaborative form of interaction which is a priority in the design of robotic aids for older adult users. The results provide some insights into shared control designs which accommodates the preferences of the older adult users as they interact with robotic aids such as the table setting robot used in this study

Keywords: Shared control, Levels of automation, transparency, collaborative robots, human-robot interaction.

1. Introduction

Robots with improved capabilities are advancing into prominent roles while assisting older adults in performing daily living tasks such as cleaning, dressing, feeding (Honig et al. 2018; Shishehgar, Kerr, and Blake 2018). This has to be done with careful consideration for the strong desire of these older adults to maintain a certain level of autonomy while performing their daily living tasks, even if the robot provides the help they require (Wu et al. 2016). Furthermore, the robot's involvement should not drive the older adult to boredom, sedentariness or loss of skills relevant to daily living due to prolonged inactivity (Beer, Fisk, and Rogers 2014). A possible solution is shared control where the user preferences are adequately considered as the robot's role and actions are being defined during the interaction design. This ensures that the older adults are not deprived of the independence they desire (Zwijsen, Niemeijer, and Hertogh 2011).

This study, proposes a shared control strategy using levels of automation (LOA) which refers to the degree to which the robot would perform particular functions in its defined role of assisting the user in a specific task (Parasuraman, Sheridan, and Wickens 2008). The aim is to ensure high quality collaboration between the older adult and the robot in accomplishing desired tasks, without undermining the autonomy, preferences and satisfaction of the older adult.

To ensure transparency of the robot's role at all times, the LOA implementation is reflected in the ways through which the users interact with the robots. Transparency in this context is the degree of task-related information provided by the robot to the older adults to keep them aware of its state, actions and intentions of the robot (Chen et al. 2018). The content of this information provided by the robot can be graded according to the detail, quantity and type of information as mirrored in Endsley's situation awareness (SA) study (Mica R. Endsley 1995) and Chen *et al.*'s SA-based Transparency model (Chen et al. 2014). It is essential that the level of transparency (LOT) of the information being presented to the older adults conforms with their perceptual and cognitive peculiarities such as the processing and interpretation of the information provided by the robot (Smarr *et al.*, 2014; Mitzner *et al.*, 2015; Feingold Polak *et al.*, 2018). Existing studies reveal that the information presented to the users significantly influences their comprehension of the robot's behavior, performance and limitations (Chen et al. 2014; Dzindolet et al. 2003; Lyons 2013). This information facilitates the users' knowledge of the automation connected to the task (Mica R. Endsley 2017b). This affects the users' understanding of their role and that of the robot in any given interaction (Chen et al. 2014; Doran, Schulz, and Besold 2017; Hellström and Bensch 2018; Lyons 2013).

Some studies explored the presentation of information through various technological aids such as digital mobile applications, webpages, rehabilitation equipment, and other facilities through which older adults would interact with their environment (Cen/Cenelec 2002; Fisk et al. 2009; Mitzner et al. 2015). These studies, provided recommendations which served as design guidelines for information presented in various modes such as visual, audial or haptic information. These recommendations are not specific to information presented by robots to the older adults. They are general guidelines recommended to aid usability as older adults interact with technological devices. It was therefore recommended in those studies that more user studies should be conducted in specific robot-assistance domains such physical support, social interaction, safety monitoring, cognitive stimulation and rehabilitation (Cen/Cenelec 2002; Fisk et al. 2009; Mitzner et al. 2015; Van Wynsberghe 2016). Through such studies, suitable design parameters could be identified that would meet the needs of the older adults in specific applications such as the table setting robot application on which this study is focused.

The aforementioned studies have explored individual effects of LOA or LOT separately in different domains. But this has not been examined in the use of socially assistive robots for older people. LOA, as a control strategy, tends to improve the collaboration between the user and the robot by sufficiently keeping the user in the loop. This is critical in older adults' interaction with robots in order to avoid inactiveness. LOT, as an information presentation strategy, also tends to improve the awareness of the user during the interaction. This is also critical for the older adults to ensure that they are constantly carried along in the interaction. We therefore hypothesize that exploring some LOA and LOT options in robot-assisted tasks could increase the engagement and satisfaction of the older adults as they interact with the robots. The current study aims to explore how LOA and LOT influences the quality of interaction (QoI) between the older adults and the assistive robot in a shared task of table setting. The QoI is a construct in this paper which entails the fluency, understanding, engagement and comfortability during the interaction.

2. Methods

Overview

A table setting task performed by a robotic arm was used as the case study. The robot had to pick up a plate, a cup, a fork and a knife and to place them at preset positions on the table. The user operated the robot in two levels of automation. In the high LOA condition, the robot operated autonomously. The user could only start and stop the robot's operation by pressing a specific button.

In the low LOA condition, the user could still start and stop the robot, but the robot required the user’s consent before setting each item. The robot asked the user through a GUI which item to bring and the user was required to respond before the robot could continue its operation.

Two conditions utilizing different levels of transparency (LOT) were compared for two different levels of the robot's automation: high and low (Table 1). Information was given by the robot in visual form through a GUI on an adjacent screen where the LOT manipulated (Figure 1). The two conditions differed by the amount of details provided by the robot. The low level of information included text messages that specified the status of the robot by indicating **what** it was doing (e.g. bringing a plate, putting a fork, etc.), while the high level of information included also the **reason** for this status (i.e. I’m bringing the plate since you asked me, etc.)

Table 2. Experimental Conditions

		LOA	
		Low	***High***
LOT	***Low***	Condition 1 – LL User instructs the robot using the GUI and receives information about **what** the robot is doing in each stage.	Condition 3 – LH Robot operates automatically. In each stage user receives information about **what** the robot is doing.
	High	Condition 2-HL User instructs the robot using the GUI and receives information about what the robot is doing and the reason for it in each stage.	Condition 4-HH Robot operates automatically. In each stage user receives information about **what** the robot is doing and the **reason** for it.

Apparatus

A KUKA LBR iiwa 14 R820 7 degrees of freedom robotic arm equipped with a pneumatic gripper was used (Fig. 1). The tasks were programmed using python and executed on the ROS (Schaefer 2015) platform.

In order to instruct the robot and to present the information received by the robot a graphical user interface (GUI) was used on a PC screen, which was located on a desk to the left of the user (see Fig. 1).

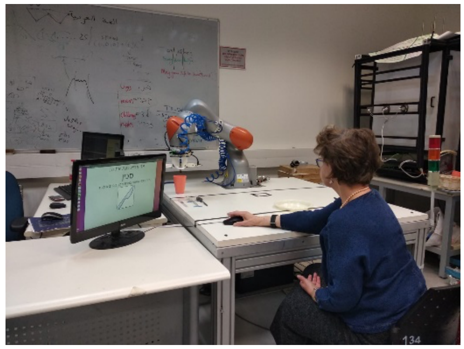


Fig. 1. A participant using the GUI to instruct the robot.

Participants

Fourteen older adults (8 Females, 6 Males) aged 62-82 (mean 69.8) participated in the study. Participants were recruited through an advertisement which was publicized electronically. They were healthy individuals with no physical disability who came independently to the lab. Each participant completed the study separately at different timeslots, so there was no contact between participants.

Experimental Design

The experiment was set with a mixed between and within subject design with the LOA modes as the between subject variable, and the LOT as the within subject variable.
Participants were assigned randomly to one of the two LOA conditions. All participants completed the same table setting task for both levels of transparency. The order of the two tasks was counterbalanced between participants, to accommodate for potential bias of learning effects, boredom or fatigue.

Performance measures

Initially, participants completed a pre-test questionnaire which included the following: demographic information, and a subset of questions from the Technology Adoption Propensity (TAP) index (Ratchford and Barnhart 2012) to assess their level of experience with technology and from the Negative Attitude toward Robots Scale (NARS) (Syrdal et al. 2009a) to assess their level of anxiety towards robots.
Objective measures that were collected during each session are interaction-related variables such as fluency, engagement, understanding and comfortability. Subjective measures were assessed via questionnaires. Participants completed a short post-session questionnaire after each session and a final questionnaire at the end of the two sessions to evaluate subjective measures. The post-session questionnaire used 5-point Likert scales with 5 representing "Strongly agree" and 1 representing "Strongly disagree". The final questionnaire related to the difference between both sessions.

Analysis

A two-tailed General Linear Mixed Model (GLMM) analysis was performed to evaluate for a positive or negative effect of the independent variables. The user ID was included as a random effect to account for individual differences. LOA and LOT were utilized as fixed factors while all objective and subjective variables representing 'Quality of Interaction' (QoC) were used as dependent variables.

3. Results

Demographics and Attitude towards Technology

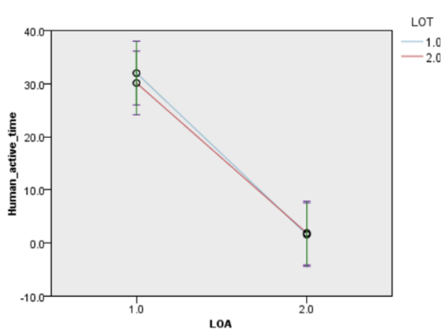
There was an equal distribution of participants within the two groups. On a scale of 1 (strongly disagree) to 5 (strongly agree), the TAP index reveal**s** that most of the participants are optimistic about technology providing more control and flexibility in life (*mean = 3.86, SD=1.17*). It was also observed that over 75% of the participants like to learn the use of new technology (*mean=3.93, SD=1.07*) and feel comfortable communicating with robots (*mean= 3.43, SD=1.50*). The majority (80%) did not have negative feelings about situations in which they have to interact with a robot (*mean = 4.14, SD = 0.86*).

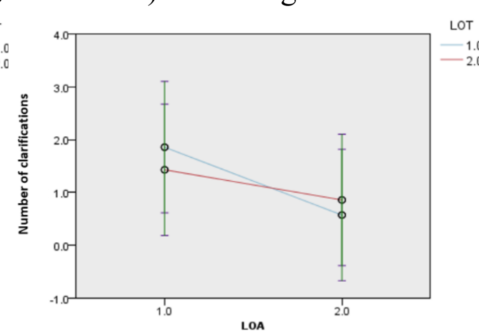
Quality of Interaction

A two-way ANOVA was run to find out if there was a significant difference between the LOA-LOT manipulation as conditions ($F(3, 22) = 2.35, p=0.033$). The effect of the manipulation was significant on the robot's idle time ($F(3, 22) = 4.91, p=0.009$), functional delay ($F(3, 22) = 21.22, p<0.001$), human idle time ($F(3, 22) = 3.03, p=0.005$), the gaze on the robot ($F(3, 22) = 3.97, p=0.021$), perception of safety ($F(3, 22) = 3.22, p=0.042$) and overall interaction time ($F(3, 22) = 5.31, p=0.007$). The effect of the manipulation was not significant on the gaze on the GUI where the robot provided feedback ($F(3, 22) = 2.01, p=0.142$). More details of the components of the quality of interaction are presented below.

Fluency

Fluency was represented by the idle time of the robot, functional delay and overall time spent on the task. The LOA was significant on the robot's idle time (*mean = 122.54, SD = 59.70*, $F(1, 24) = 9.97, p=0.004$) with the high LOA (*mean=88.85, SD=2.48*) having a lower robot idle time compared to low LOA (*mean 156.21, SD=70.38*). The LOT was not significant as a main effect but there was a significant effect in the interaction between the LOA and LOT ($F(4, 24) = 44.2, p<0.001$) as depicted in Fig. 3. In terms of delay (*mean = 12.86, SD = 13.87)*, the LOA was significant ($F(1, 24) = 14.48, p=0.001$). The low LOA had more delays (*mean=20.85, SD=15.99*) than high LOA (*mean=4.87, SD=13.87*). The LOT was not significant ($F(1, 24) = 2.04, p=0.17$). There was also no interaction effect of the LOA and LOT on the delays ($F(1, 24) = 1.49, p=0.23$). The duration of the experiment with low LOA (*mean=239.21, SD=74.41*) were longer than that with high LOA (*mean=158.53, SD=66.17*). This was also statistically significant (*mean = 198.53, SD = 66.17*, $F(1, 24) = 15.42, p=0.001$). The results therefore suggest that high LOA influenced more fluency in the interaction than low LOA.





Engagement

The duration of the gaze on the robot was significantly affected by LOA (mean = 155.64, SD = 34.51, p=0.006). Participants in low LOA (mean=175.57, SD=34.77) gazed on the robot more than participants in high LOA (mean=135.71, SD=20.22). The interaction between LOA and LOT on the time participants gazed on the robot was significant (F(1,24)=7.83, p=0.01). Participants in low LOA (mean=35.50, SD=17.81) were also more significantly focused on the GUI (mean = 27.01, SD = 19.60, p =0.037) than participants in high LOA (mean=18.643, SD=18.10). The interaction between LOA and LOT was significant regarding the focus on GUI (F(1, 24) = 4.48, p=0.045). The effect of LOA on the human's active time was also significant (mean = 16.39, SD = 16.62, p<0.001) with low LOA (mean = 31.07, SD=10.47) keeping the human more active than the high LOA (mean=1.71, SD=0.82). There was an interaction effect between the LOA and LOT (F(1, 24) = 47.28, p<0.001).

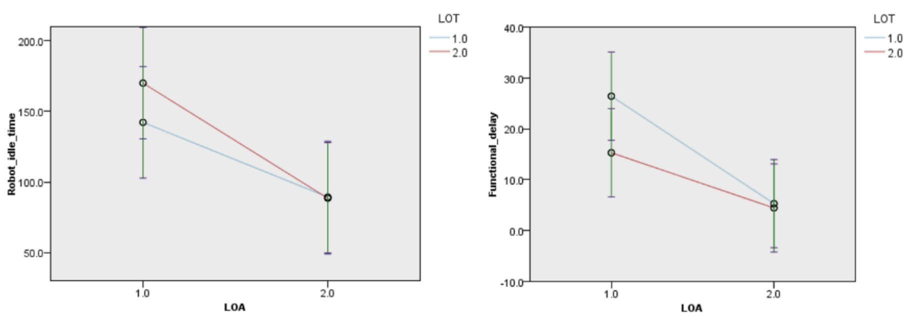


Fig. 2. Interaction effect of LOA and LOT on various some QoI variables

Understanding

There was no significant difference in the number of clarifications made by the participants during the interaction (mean=1.18, SD=1.59, p=0.124) as a result of the LOA manipulation. The participants seemed to understand the status of the interaction and actions of the robot in both LOA and LOT modes (F(1, 24) = 2.27, p=0.15). Only a few participants asked for clarification at the low LOA (mean=1.64, SD=1.95) and high LOA modes (mean=0.71, SD=0.99). However, in terms of reaction time of the participants as the robot interacted with them, the LOA was significant (mean = 12.86, SD = 13.87, p=0.001). The participants spent more time observing and processing the information the robot was presenting to them as consent in the low LOA (mean=20.85, SD=15.99) compared to the high LOA (mean=4.87, SD=13.87).

Comfortability

The effect of the LOA and LOT did not influence the heart rate of the participants. But it was also not significant on the comfortability of the participants with regards to their perception of safety of the robot (*mean = 2.54, SD = 0.58, p =0.48*). However, it was observed that participants in low LOA moved much closer to the robot which represented more comfortability with it than participants in high LOA which sat further away from the robot.

4. Discussion and Conclusion

Most of the participants were comfortable interacting with a robot. The results revealed that the quality of interaction, as measured via fluency, engagement, understanding and comfortability of the interaction was influenced mainly by the interaction of LOA and LOT. The main effect of LOA had less influence compared to that of the main effect of LOA but the interaction of LOA and LOT was significant across most of the variables. Participants seem to prefer less information (low LOT) when the robot was operating more autonomously (high LOA). They also seem to prefer more information (high LOT) when they were more active with the robot such as the case in low

LOA mode. This agrees with the findings in (Chen et al. 2018) where differences were not found in the transparency level that included only status information and reason without LOA involved. In current study where the level of involvement of the participant varies with the LOA, it is noteworthy that the LOT preferred is influenced by the LOA the robot is operating in.

This corroborates the characteristics of the visuospatial sketchpad (VSSP) working principle as modelled by Baddeley (A.D. Baddeley et al. 1975; Alan D. Baddeley 1986, 1997). It suggests a dissociation within the VSSP, between active operations such as the movement of the robot and a passive store of information as the information displayed on the GUI (Bruyer and Scailquin 1998). Even though, there is a high cognitive demand on the participants when actively involved with the robot in a low LOA mode, the participants still handle more information (high LOT) since the information display was passive. This is in contrast to the scenario where the robot was more autonomous (high LOA), with less cognitive demand on the participant.

Future research should advance a longitudinal study, to increase familiarity with the robot operation and overcome the suspected naivety effect (Kirchner and Alempijevic 2012; Shah and Wiken 2011) of the older adults with the robot. We expect that the more the older adults get familiar with the operation of the robot, their level of trust in the robot may change and thus cause a change in their LOT demands as well.

According to the participants' recommendations more awareness might be improved through voice feedback. This possibility is also supported by the suggestion of (Sobczak-Edmans et al. 2016) indicating that some form of verbal representation of information supports visual representations. This should be explored in future work to improve the shared control of the older adult with the table setting robot.

Previous research in human robot collaboration discovered the effectiveness of coordination in team performance as presented in (Shah and Wiken 2011). Our work further presents the potential of LOA in improving quality of interaction. This is reflected in the various objective measures taken for engagement, fluency, degree of involvement and comfortability with the robot where the LOA effect was significant. The low LOA enabled the participant to interact more with the robot by selecting the specific item that the robot should pick up and the order of arrangement. This inspired greater collaboration with the robot. It enhanced the concept of shared control where the user is more involved in the decisions and control of the robot's operations. This is very critical to ensure that the older adult keeps active so as not to lose skills or functionality of the muscles (Wu et al. 2014). This corresponds with the "use it or lose it" logic presented by (Katzman 1995) in their study of older adult lifestyle.

Most studies which included some form of adaptive coordination to improve the collaboration between the robot and the user (Huang, Cakmak, and Mutlu 2015; Someshwar and Edan 2017) tried to reduce the completion time of the task. There was a trade off in this current study regarding degree of involvement and time to complete task i.e., at a higher degree of user involvement, more time was spent to complete the task. It is noteworthy that the focus for the target population is to ensure user involvement to avoid idleness and other negative outcomes of sedentariness and not speed. Moreover, most participants expressed enjoyment, and pleasure as they interacted with the robot, which suggests other reasons for the longer interactive time. This can therefore be considered as a positive outcome of the interaction and a favorable contribution to improve shared control in human-robot interaction scenarios such as this.

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Chapter 4: Influence of LOA and feedback on QoI

Levels of automation and feedback modality development in an assistive robotic table clearing task robot for older adults

Evaluating levels of automation and feedback in an assistive robotic table clearing task for eldercare

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1 Introduction

Eldercare encompasses various activities involved in caring for older adults to meet their physical, cognitive, emotional and social needs (J. M. Bauer and Sousa-Poza 2015). These activities are commonly represented as activities of daily living (e.g. bathing, hair care), instrumental activities of daily living (e.g. cleaning, meal preparation) or enhanced activities of daily living (e.g. learning new hobbies, or assistance with new skills) (C. A. Smarr et al. 2012). To ensure that older adults enjoy their independence at home, these activities need to be adequately catered for (Allaban, Wang, and Padir 2020). There is a growing percentage of older adults who need help with these activities while the number of people available to care for them and assist them with these activities is declining (Bogue 2013). This foreshadows an 'elder care gap', which research over the years regarding possible solutions, has revealed that assistive robots could play a vital role in forestalling (Allaban, Wang, and Padir 2020; C. A. Smarr et al. 2014).

Assistive robots are robots that generally provide support to a human user (Pfeil-Seifer and Mataric 2005). One of the major applications is in eldercare where some robots are currently being developed to assist the older adults in daily care (C.-A. Smarr, Fausset, and Rogers 2010), rehabilitation (Burgar et al. 2000), ambulation (Glover et al. 2003) and companionship (Roy et al. 2000)). With regards to daily care, previous studies have shown that the older adults were generally more open to robotic assistance in instrumental activities of daily living with activities such as cleaning and clearing emerging as one house chores where support is needed (Hall et al. 2019; C. A. Smarr et al. 2012, 2014). There are, however, very limited robots available for the variety of cleaning and clearing tasks in homes apart from floor cleaning robots (Prassler et al. 2000). This reveals the need for more robotic developments in the area of cleaning and clearing as one of the major domestic chores where the older adults need support (Prassler et al. 2000; C. A. Smarr et al. 2014).

Robot-aided table clearing, as an example of robots supporting with cleaning and clearing tasks, involves the assistive robot providing assistance in taking away certain items from the table with the consent of the user without overriding the preferences of the user (Masuta, Hiwada, and Kubota 2011). The focus over the years has been on the development of the software, hardware and control architecture necessary for the robot to successfully perform this task (Suzuki et al. 2019). These developments have contributed immensely to the capabilities of the robot to perform object identification and manipulation as it takes items from the table (Masuta, Hiwada, and Kubota 2011; Scopelliti, Giuliani, and Fornara 2005). While these developments have largely emerged successful (Chong et al. 2004; Suzuki et al. 2019), only very minimal studies have investigated the interactive role the robot plays in the different phases of the table-clearing task particularly for a sensitive population like older adults (J. M. Bauer and Sousa-Poza 2015; M. J. Johnson et al. 2020; Portugal et al. 2019; Zafrani and Nimrod 2019b).

It is pertinent that the autonomy of the older adults is considered carefully in the development and operation of these table-clearing robots to ensure that the older adult user still stays in control of the process without being overburdened by the task (Czaja et al. 2009). This ensures that their interests, preferences and active engagements in the process are maintained while avoiding dissatisfaction (D. B. Kaber 2018), frustration (Scopelliti, Giuliani, and Fornara 2005) or a sedentary lifestyle which could evolve as a result in an unbalanced robot-user role allocation process (Czaja et al. 2019). This brings to the fore the need to ensure a balance in the roles of the robot to avoid extremes of overreliance on the robot, misuse or disuse of the robot's automated capabilities (Parasuraman and Riley 1997). A strategy proposed and tested over several years of research in different domains is through introduction of appropriate levels of automation which can be generally defined as the degree to which automation is employed in the task (Sheridan and Verplank 1978). In this context of eldercare robot-aided table clearing, it can be explained as the extent to which the robot participates in the task of clearing the table. This ensures that the autonomy of the older adult is considered in the process of aiding in the task (Beer, Fisk, and Rogers 2014).

It is also crucial that the older adult is carried along regarding the robot's activities as it carries out the task (Beer et al. 2012; Hellström and Bensch 2018), which connects with feedback provided by the robot (Lyons 2013). Feedback can be defined in this context as the information provided by the robot to the user regarding its intentions, reasoning, plans and actions (Nicole Mirnig and Manfred 2015). This information could be encoded in different formats (visual, audial, haptic or a hybrid) through which the robot communicates the information to the user (N Mirnig, Weiss, and Tscheligi 2011). This formats, which in this study is referred to as feedback modes differ in their capacity to convey the required information to the older adult population who have their peculiarities, age-related differences and perception-related challenges (Cen/Cenelec 2002). The applicability of these feedback modes may also differ with consideration for LOA mode the robot is operating in. This underscores the aim of this study which is to develop and evaluate the influence of LOA modes and feedback modality in the interaction of older adults with a table-clearing robot while identifying suitable LOA-feedback mode combinations that would facilitate successful and satisfactory interactions.

2 Methods

2.1 Overview

The current research deals with the application of three different levels of automation and three modes of feedback in the robotic table-clearing task. The task involved the robot taking clearing eating utensils (e.g. a plate, fork, knife) and placing them at another location. The LOA and mode of feedback were the independent variables evaluated while performance in the interaction and perception of the users were assessed as dependent variables. The experimental system, development of LOA and feedback modes as well as the evaluation in user studies are described in the following subsections.

2.2 The experimental system

The system consisted of a table clearing robot, the interface for communicating with the robot and the older adults users. The robot used was a KUKA LBR iiwa 14 R820 which had 7 degrees of freedom and was equipped with a pneumatic gripper was used (Figure 1,2). Lifting load: up to 14 kg, number of degrees of freedom: 7, self-weight: 30 kg, temperature Ambient temperature: 45-5 ° C, mounting positions: floor, ceiling, wall.

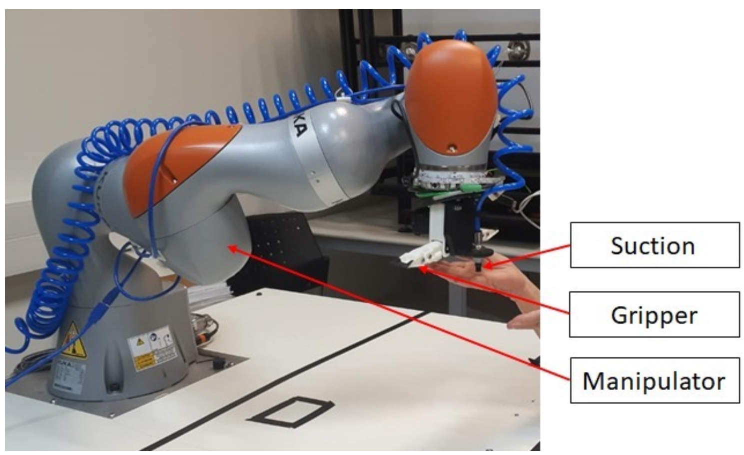

Figure 3. KUKA robot

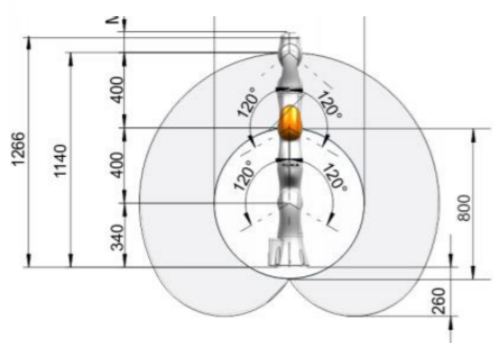

Figure 4. The angle's range

The tasks were programmed using python and executed on Robot operating system (ROS) platform (Schaefer 2015). The transfer of the tools the robot to the elderly was done by means of an air pressure vacuum except for the cup which was transferred by gripper. This interface was setup with Raspberry Pi. In order to instruct the robot and to provide feedback, a graphical user interface (GUI) was developed and used on a PC screen, which was located on a desk to the left of the user (Figure 4).

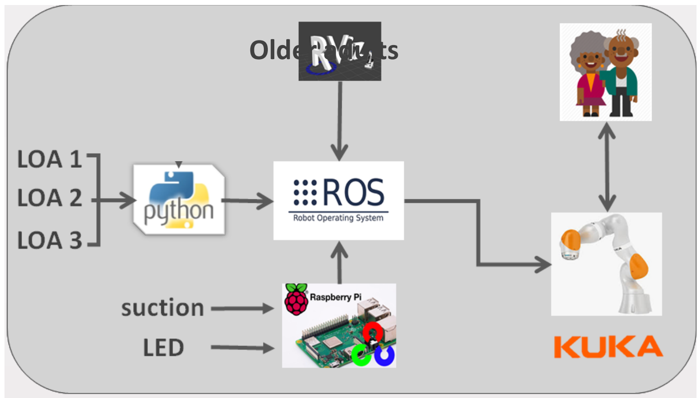

Figure 5. The system

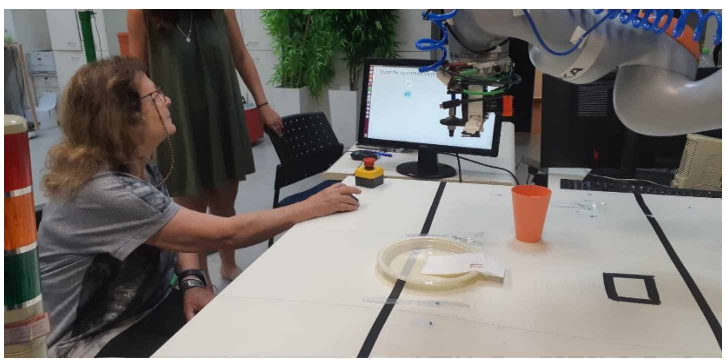

Figure 6. A participant using the GUI to instruct the robot

2.3 LOA modes

The overarching goal in the LOA development was to ensure that the older adults remain in the loop of the robot's operation at every LOA level and to maintain the availability of the robot to support at every level. This was implemented by varying the robot's degree of involvement in the decisions required for the table clearing task across each of the LOA modes. These decisions include when to start the process of clearing, what items to take, when to take specific items and when to stop in the process. This details for each of the LOA modes are given as follows:

i. High LOA: This was the highest degree of robot involvement in the decision making and the least user involvement. The robot performs the entire task of clearing the items on the table once the user initiates the process. The user is minimally involved to start the process and also to stop the robot at any point by pressing the STOP button. The flowchart for process development is provided in Figure 4.

ii. Middle LOA: This was a moderated degree of robot involvement in the decision making with more human involvement than the high LOA. The robot seeks the consent of the user before taking each item from the table. The robot suggests removing specific item and the user has to approve the action. If approved, the robot will perform the operation. If the offer is not approved, the robot offers take another item on the table till all items have been considered. The flowchart depicting this process is shown in Figure 3.

iii. Low LOA: The user's degree of involvement in the decision making is highest while the robot acts on the decision of the user. The user initiates the process, decides an item s/he desires to take off the table and instructs the robot to clear the desired item. The robot clears the item requested and waits for the next instruction without suggesting any specific item to be cleared. The human makes most of the decisions involved in the process.

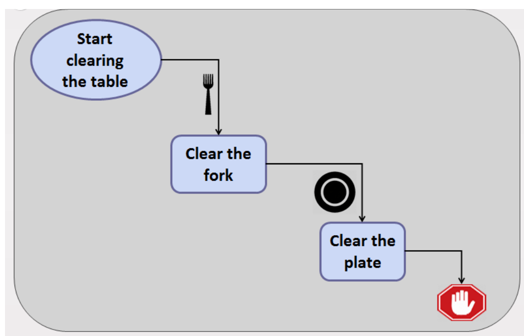

Figure 7. High LOA

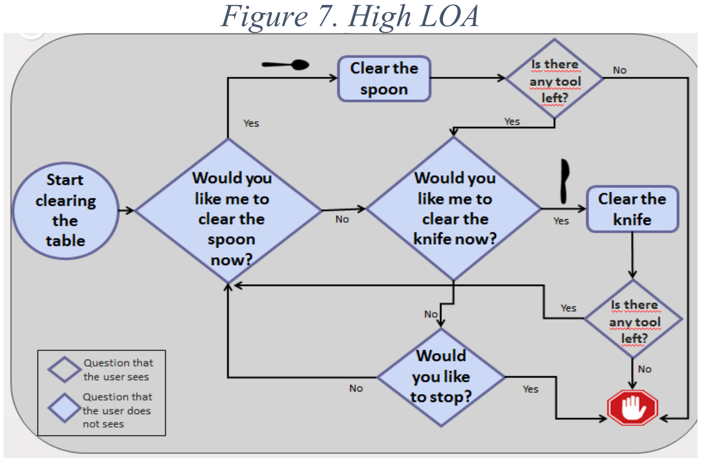

Figure 8. Middle LOA

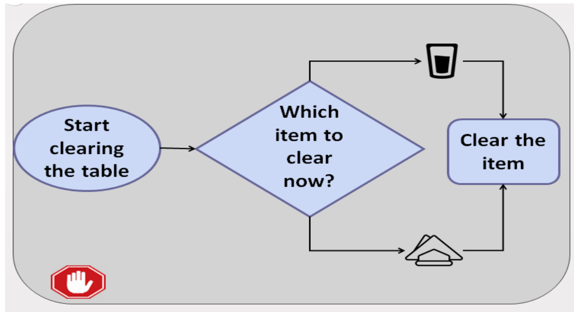

Figure 9. Low LOA

2.4 Feedback modes

The feedback was designed to ensure that sufficient information is provided to the older adult users to keep them informed (Mirnig et al., 2014) and at the same time not overloading them with information (Lyons, 2013). The three feedback modes implemented to operate at the three LOA modes are described as follows:

i. GUI screen. Each time the robot brought a certain tool to an elderly person, a message appeared on the GUI screen detailing it. (Figure 8)

ii. Led lights. Each time the robot brought a certain tool to an elderly person, the LED lights on the end of the robotic arm turned green. (Figure 9)

iii. Voice recordings. Each time the robot brought a certain tool to an elderly person, a recording was heard detailing what the robot was doing.

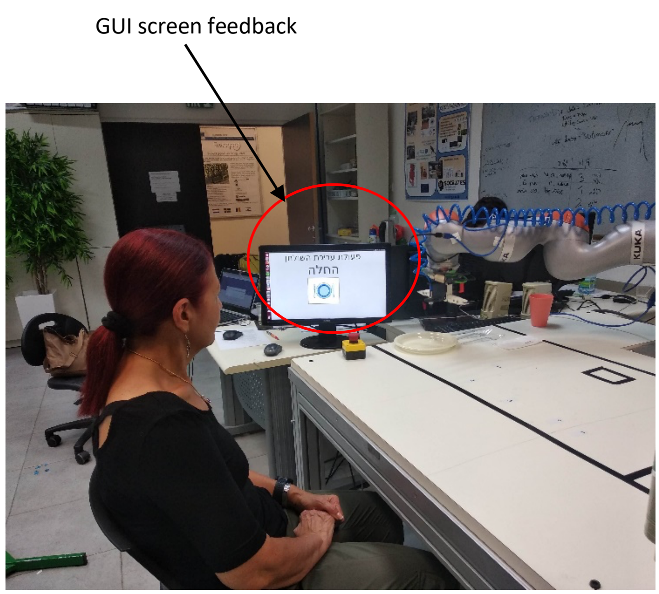

Figure 10. A participant experiences LED light feedback from the robot

Figure 11. A participant experiences LED light feedback from

2.5 Participants

22 older adults (9 Females, 13 Males) over the aged 70 (mean:74, SD:4.12) participated in the study. Participants were recruited through an ad which was publicized electronically. They were healthy individuals with no physical disability who came independently to the lab. Each participant completed the study separately at different timeslots, so there was no contact between participants.

2.6 Experimental Design

The experiment was set with a mixed between and within subject design with the LOA modes as the within subject variable, and the feedback type as the between subject variables.

Participants were assigned randomly to one of the three feedback types conditions. All participants completed the same table clearing task for the three levels of automation. The order of the three iterations was counterbalanced between participants, to accommodate for potential bias of learning effects, boredom, or fatigue.

Table 3. Experimental Conditions

		LOA		
		Low	***Middle***	***High***
Feedback	***GUI screen***	Condition 1 – LG **User choose which** item the robot clear for him each time and receives visual feedback through **GUI screen**	Condition 4-MG **User choose if approve** the item the robot clear for him each time and receives visual feedback through **GUI screen**	Condition 7-HG **Robot operates automatically**. User receives visual feedback through **GUI screen**
	Led lights	Condition 2-LL **User choose which** item the robot clear for him each time and receives visual feedback through **Led lights**	Condition 5-ML **User choose if approve** the item the robot clear for him each time and receives visual feedback through **Led lights**	Condition 8-HL **Robot operates automatically**. User receives visual feedback through **Led lights**
	Voice recordings	Condition 3-LV **User choose which** item the robot clear for him each timeand receives audial feedback through **Voice recordings**	Condition 6-MV **User choose if approve** the item the robot clear for him each time and receives visual feedback through **Voice recordings**	Condition 9-HV **Robot operates automatically**. User receives visual feedback through **Voice recordings**

2.7 Performance measures

Initially, participants completed a pre-test questionnaire which included the following: demographic information, and a subset of questions from the Technology Adoption Propensity (TAP) index (Ratchford and Barnhart 2012) to assess their level of experience with technology and from the Negative Attitude toward Robots Scale (NARS) (Syrdal et al. 2009a) to assess their level of anxiety towards robots.

Objective measures that were trial are collected during each interaction-related variables and included effort, accuracy, efficiency, engagement, comfortability, fluency, understanding as detailed below. Subjective measures were assessed via questionnaires and included reliability, satisfaction, understanding, engagement, and comfortability. The combination of these represents the dependent variable of the study – QoI.

The details of the measures are listed in table 2.

Table 4. Dependent Variable

	Dependent Variable	Measurement
Objective measures	**Effort**	Heart rate change
	Accuracy	Number of errors that occurred during the task
	Efficiency	$Efficiency = \frac{1 - total\ time\ of\ trial\ i}{max\{total\ time\ of\ trial\ i\}}$ i - trial number
	Engagement	Gaze duration at GUI - The length of time the subject looked at the robot
		Gaze duration at the robot - The length of time the subject looked in the direction of the GUI screen
		Gestures - The number of gestures performed by the subject towards the robot during the mission
	Comfortability	A categorical variable between 1-3 represents the proximity of the subject to the robot. Where 1 represents a distance away from the robot and 3 represents a very close proximity so that the subject touches the mission table surface.
	Fluency	Subject idle time
	Understanding	The number of questions asked by the subject during the assignment.
	Order LOA	A categorical variable between 1 and 3 representing the order of the automation levels experienced by the subject.
Subjective measures	**Reliability**	How much the person relied on the robot
	Satisfaction	The amount of satisfaction the person experiences
	Understanding	The extent to which the person understood the task

Engagement	The level of involvement of the subject in the task
Comfortability	The amount of comfort the person experiences

Participants completed a short post-session questionnaire after each session and a final questionnaire at the end of the three sessions to evaluate subjective measures. The post-session questionnaire used 5-point Likert scales with 5 representing "Strongly agree" and 1 representing "Strongly disagree". The final questionnaire addresses the differences felt by the participants between the different trial (examines whether they felt a difference between the different levels of automation).

2.8 Model and hypotheses

We examined which LOA enhances the Quality of Interaction (QoI), a combined dependent variable defined as a combination of subjective measures listed earlier (Figure 10).

The hypotheses of the experiment:

H1: LOA will affect the quality of the interaction between the user and the robot

H2: Feedback will improve the quality of interaction between the user and the robot

H3: Feedback will improve user interaction with the robot at higher LOA

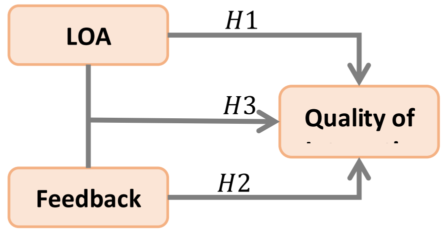

Figure 12. The Model

2.9 Analysis

A two-tailed General Linear Mixed Model (GLMM) analysis was performed to evaluate for a positive or negative effect of the independent variables. The user ID was included as a random effect to account for individual differences. LOA and feedback type were utilized as fixed factors while all objective and subjective variables representing ‘Quality of Interaction’ (QoI) were used as dependent variables.

3 Results

3.1 Demographic Analysis

The study population included 21 older adults, 8 females and 13 males, aged 70 to 86 (mean=74.1, SD= 4.12). Two of the participants possess a Ph.D., 5 have a master’s degree, 8 own bachelor’s degrees, 7 have a high school-based education and 3 are of alternative education.

3.1.1 TAP - Technology Adoption Propensity

Result shows that 75% of the participants firmly believe that technology provides increased control and flexibility in life. Although 40% of the participants noted low self-confidence regarding the general sense of being technological, as well as regarding the ability to quickly and easily learn operation of innovative technologies. Only 5% of the participants obtain high confidence in said ability, the remaining 20% remain indifferent. Nevertheless, 75% of the participants reported that they enjoy acquiring new technological skills and only 5% said otherwise do not. Furthermore, 40% of the participants believe that they are being overly dependent on technology and are even enslaved by it, while 27% have a neutral opinion.

3.1.2 NARS – Negative Attitude toward Robots Scale analysis

Regarding attitude towards robots, 20% of the participants have a low scale negative view of robots, 20% have a high scale negative attitude while 60% are neutral. The mean is 13.5 and the standard deviation is 5.56. Additionally, 20% have highly negative attitudes toward situations which include robots, 30% are neutral while 50% have low negative attitude toward such situations. Apparently, 30% have highly negative attitudes toward robot’s social influence whereas 70% are neutral. Finally, 30% have a highly negative attitude toward the concept of robots having emotions, 40% are indifferent and 30% have a low scale negative attitude towards it.

3.1.3 Demographics and Attitude towards Technology

The study population consists of 21 older adults, 8 females and 13 males, aged 70 to 86 (mean=74.1, SD= 4.12). Two of the participants possess a Ph.D., 5 have a master’s degree, 8 own bachelor’s degrees, 7 have a high school-based education and 3 are of alternative education.

Result shows that 75% of the participants firmly believe that technology provides increased control and flexibility in life, Although 40% of the participants admitted to low self-confidence regarding the general sense of being technological, as well as regarding the ability to quickly and easily learn operation of innovative technologies. Only 5% of the participants obtain high confidence in said ability, the remaining 20% remain indifferent. Nevertheless, 75% of the participants reported that they enjoy acquiring new technological skills and only 5% said otherwise do not. Furthermore, 40% of the participants believe that they are being overly dependent on technology and are even enslaved by it, while 27% have a neutral opinion.

3.2 User perception

From the questionnaires performed at the end of each trial, it appears that 86% of the respondents indicated that they were not at all stressed about cooperation with the robot, while 7% indicated that the cooperation experience was stressful for them. Satisfaction of subjects in the collaboration between them and the robot can be seen in Figure 7. It can be seen that the vast majority of the subjects (18 participants in the high LOA, 17 in the middle LOA and 15 in the low LOA) testified that they were most satisfied with the collaboration between them and the robot (Figure 11).

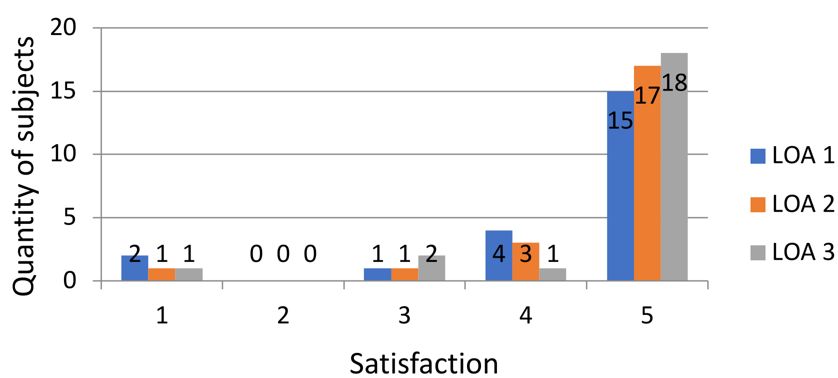

Figure 13. Quantity of subject vs. Statisfaction

When respondents were asked whether they had relied on the robot during the mission, 56% indicated that they had fully trusted the robot, while a considerable 11% said they did not feel trust. This can be related to the fact that participants who testified that they relied on the robot at a low level were in cases where they testified that the robot had made a mistake during the mission. Correspondingly, the Pearson correlation between the results of the robot's reliability level question and the results on number of errors the robot performed in the person's opinion, is a high negative correlation of -0.426. In other words, the more the robot makes mistakes, the lower the level of reliability of the subject in the robot.

Results of the final questionnaire at the end of the experiment showed that the level of automation preferred by most subjects (50%) was the highest level of automation as can be seen in Figure 12.

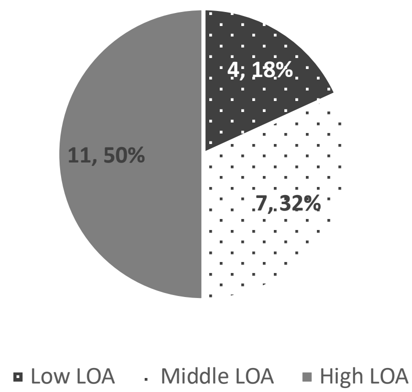

Figure 14. LOA preference

Additionally, most subjects (41%) indicated that they would very much like to use the robot in a daily task, such as clearing the table. However, many other subjects (27%) indicated that they were not interested in using such a robot in their home. Which may explain from what came up in the demographic questionnaire that many of the adults testified that they are admitted to low self-confidence regarding the general sense of being technological

Order Effect

An ANOVA test (P=0.003) indicating that in which the subjects experienced the levels of automation (which was random for each subject) had an impact on their satisfaction, and ultimately on the level indicated as preferable in the final questionnaire. Post Hoc test (P=0.002) revealed that the difference in preferences was when the order of LOA does not occur in chronological order: 2->1->3 or 3->1->2.

Results reveal that the automation level had significant effect on most of the performance measures. Feedback, and the interaction variable between the levels of automation and the feedback did not have a meaningful effect on most measures.

None of the independent variables had significant effect on effort, gaze robot, comfortability and understanding (Table 3). LOA had significant effect on accuracy (M=0.18, SD=0.39), efficiency (M=70.21, SD=14.69), gaze GUI (M=17.96, 11.84) and fluency (M=57.13, 14.63). Feedback and the interaction variable between LOA and Feedback (Feedback*LOA) had significant effect on accuracy.

Table5 . Significant variables

	Effort	Accuracy	Efficiency	Engagement	
	HR	Errors	Total time	Gaze GUI	Gaze robot
LOA	.912	.012	.000	.000	.009
Feedback	.128	.037	.819	.465	.587
LOA * Feedback	.376	.012	.861	.747	.938

	Fluency	**Comfortability**	**understanding**
	Human idle time	Proximity	Questions
LOA	.001	.134	.101
Feedback	.244	.082	.723
LOA * Feedback	.545	.738	.150

Nevertheless, an interesting statistic identified that the interaction variable had a significant effect (P=0.017) on the transaction index measured by the amount of gestures the person made to the robot during the mission (Figure 13). This can be explained by combining an automation level with feedback, hence a person feeling more involved in the task and acting accordingly, making more gestures during the task. Figure 8 shows the difference in the effect of each level of automation with a specific feedback type, on the amount of gestures the person made to the robot during the task. Primary, we can conclude that at the highest level of automation the difference is the most significant (green line). This information makes sense considering controlling most of the robot increases the importance of feedback, since that is what keeps the person within the task and gives him the feeling that he is involved. If we examine the type of feedback, it appears that at the high level of automation, when the feedback type was voice recordings, the difference is most significant. This is justified in literature seeing as it is known that voice feedback, versus visual feedback, makes the user feel that the feedback is more human and as a result becomes more involved in the task.

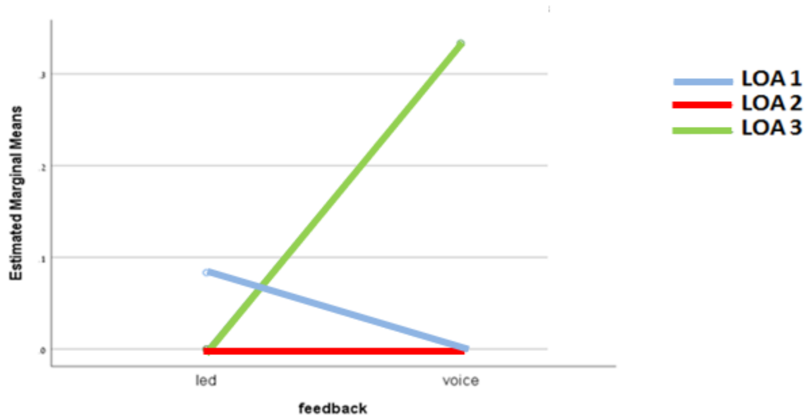

Figure 15. Number of gestures at the level of automation with feedback type

3.3 Qualitative analysis

During the running of the experiments, it was possible to notice the nuances of the interaction of the adults with the robot according to the sentences they said.
In term of trust, most adults who experienced a low and then high level of automation felt that control was taken away from them and said sentences like: "Why is he not listening to me this time?", "Let's see if he turns the tool I want". This reinforces what was said in the quantitative analysis of the questionnaires.
In terms of adult preferences, most testified that they were happy for a similar robot in their home that would help with daily tasks. One participant said, "oh this robot knows better than me".
But some shared that the specific robot with which they experienced the experiment – the KUKA, is too large for storage in their home and unsuitable. They were happy for a more compact robot to perform the same operation.

4 Discussion and conclusions

The system demonstrates feedback and LOA design aspects especially suited for older adults in an assistive robot task. The experimental results give insight into daily task of clearing a table that older adults would prefer a robot to assist with. Most of the participants testified that they would like a similar robot in their home to assist them, emphasizing the relevance of the developed system. This is consistent with previous research that older adults expressed interest in the robot assisting with difficult tasks, saving time, performing undesirable tasks, reducing effort, and performing tasks at a high-performance level (Fausset at el., 2011). For an older adult to accept technology, such as robotics, the benefit has to be clear (Ezer at el., 2007; Caine at el., 2009). Many of these tasks were physical in nature (e.g., cleaning kitchen or Bathroom) (J. M. Beer et al., 2012).
However, a significant percentage reported that they would not want such a large robot in their home since they do not think it will suit them. Many of the older adults reported that they lived in

a condo or apartment home, where storage was limited. Therefore, the robot design must be adapted to fit the working environment constraints.

Most of the participants were comfortable and trusted the robot. Trust is an essential element for older adults and robot care providers to work effectively.
The vast majority of the participants felt the difference between the various levels of automation, and noted preference for the highest level of automation.
The integration of feedback during the task increases the participant's involvement, especially at a high level of automation. The subjects indicated that their preferred type of feedback was voice recording feedback. Some respondents suggested to consider the timing of giving feedback. They recommended that the robot first performs the task and then provides the feedback rather than vice versa.
The GUI screen feedback for this task was less relevant for older adults because they rarely looked at the screen probably because they were concentrated on the robot. Therefore, it is recommended to investigate into other types of feedback. However, this also might be due to the novelity effect, after a certain period of time they might become accustomed to the robot and prefer visual feedback like a GUI screen.

when an adult has control during the task and then it is taken some way, it affects the quality of interaction between the adult and robot and reduces his/her satisfaction. Thus, it is recommended to gradually increase control to the adult. This reinforces the initial suspicions that when subjects first experience a low level of automation (ie, the subject has more control over the task) and then experience a higher level of automation (ie control was taken from them), their satisfaction was reduced which also affected the preference level indication. The subjects expressed sentences such as, “But why did the robot not ask me this time what I wanted?”, “The robot does not listen to me”, etc.

Further studies to improve the system and further its’ development with the objective of maximizing the quality of interaction between robot and elderly can address different aspects such as personal adaption of the level of automation and type of feedback and dynamic adaption of LOA along performance (depending on experience, fatigue).

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Chapter 5: Influence of LOA, LOW and LOC on QoI

Levels of automation for different levels of workload and task complexities in human-robot collaboration

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Abstract. This study explored how different levels of automation (LOA), workload and task complexity influence the interaction between a human and a robotic arm in a collaborative assembly task. Evaluation was conducted through a user study involving 80 participants. Two LOA modes were designed, implemented, and evaluated in an experimental setup for two different workload levels and task complexities. User preferences regarding the LOA modes in the different workload and task complexity conditions were assessed. In addition, two constructs were specially designed for the evaluation: quality of task (QoT) execution and usability. These constructs were measured objectively and subjectively through several dependent variables and combined using principal component analysis. Results revealed that most of the participants preferred the low LOA at high complexity and high LOA when the workload increases. The quality of task execution was also better at high LOA when workload is high irrespective of the task complexity, but the usability results reveal the benefits of low LOA in situations when task complexity changes. The outcome provides some insights into shared control designs which accommodate user preferences in the workload and task complexity situations that may arise in the collaboration with the robot.

Keywords: Levels of automation, workload, complexity, collaborative robots, human-robot collaboration, usability, quality of task execution.

1. Introduction

Human-robot collaboration

Human–robot collaboration (HRC) generally involves one or more humans working with one or more robots to accomplish a certain task or a specific goal (A. Bauer, Wollherr, and Buss 2008). This collaboration is a subset of human-robot interaction which more broadly involves understanding, designing, and evaluating robotic systems for use by or with humans (Goodrich and Schultz 2007). Effectiveness of HRC can be evaluated by the accuracy and completeness of the task which the human and robot cooperate to execute (ISO 2018). This collaboration is commonly described as efficient when minimal resources such as time and human effort are expended to achieve the required goal (Baraglia et al. 2016). To ensure that the human can successfully team up with the robot to achieve such collaboration, the human's perception regarding ease of use is essential (Bröhl et al. 2019). Ease of use in this context refers to the degree to which the human operator believes that working with the robot will be free of difficulty or great effort (Davis 1989). A negative user perception regarding this ease of use could lead to disuse of the support the robot can provide in the collaboration (Parasuraman and Riley 1997). It is therefore necessary to consider the factors that can potentially affect the effectiveness, efficiency and ease of use in HRC when designing human robot collaborative tasks (A. Bauer, Wollherr, and Buss

2008; G. I. Johnson and Wilson 1988). It is also crucial to evaluate the effect, characteristics and implications of these factors through extensive user studies to ensure the users' point of view, preferences and peculiarities are considered in the design (Kaber, 2018). This contributes to the development of detailed, accurate and user-tested models of HRC that increases the potential for successful collaboration and higher user acceptance (Bröhl et al. 2019; Feigh 2011)

The capabilities of robots have increased significantly such that with high precision, they can repeatedly perform specialized tasks without performance deterioration even in complex environments, with heavy workload (Wang, Kemény, Váncza, & Wang, 2017). However, there are still limitations the robots encounter in some areas particularly when handling unexpected situations (Monostori, Váncza, and Kumara 2006). Humans, on the other hand, usually respond to unexpected situations better and resolve such situations with more dexterity, even in complex and dynamic tasks (Wang et al., 2017). But, humans are more prone to stress or fatigue and errors particularly in high workload situations (Arai, Kato, and Fujita 2010). One of the motivations of HRC therefore, is to bridge the gaps in skills and operational characteristics such that the human and robots work cooperatively as partners (Fong, Thorpe, and Baur 2007). This partnership harnesses the combination of the complementary strengths, skills and intelligence of both the human and robot resulting in increased quality of task execution alongside, robustness and improved flexibility and work ergonomics (Wang et al., 2019).

HRC in assembly tasks

HRC in assembly tasks usually involves a robot retrieving an object for the human, holding the object for a designated time, laying it aside, placing or fixing in a required position (A. Bauer, Wollherr, and Buss 2008). There are a variety of HRC techniques and advances that have emerged in recent years for different kind of assembly tasks. In automotive assembly tasks, as an example, cooperating robots for precise material handling and secondary assembly operations have been advanced to increase the precision and speed of the automation while accommodating the dexterity and intelligence of the human operators (Smets 2019). Dual arm robots have also been explored for various bimanual assembly tasks to improve stability flexibility and cooperation between the robot and the human (Krüger, Schreck, and Surdilovic 2011).

In some other HRC assembly tasks such as computer assembly tasks, a form of symbiotic HRC has been investigated featuring the interplay of the human and the robot in a cyber-physical shared work space (Wang et al., 2019). This enabled better combination of complementing competencies to resolve complications in complex work environments (Nikolakis, Maratos, and Makris 2019). The effect of temporal and spatial relation of collaborating humans and robots in industrial production settings has also been researched to identify design considerations for situations where collaborating agents share (or partially share) the same space (Hoffman 2019; Krüger, Lien, and Verl 2009; Someshwar and Edan 2017).

Factors influencing HRC assembly tasks

The level of automation (LOA) of the system, defined as the degree to which the robot and the human are involved in the collaborative task (Endsley & Kaber, 1999; Lindström, Winroth, & Stahre, 2008; Shi, Jimmerson, Pearson, & Menassa, 2012) influences the characteristics of the HRC (Burke, Murphy, Rogers, Lumelsky, & Scholtz, 2004; Wang et al., 2017). This affects the dynamics of the collaboration, the behaviour of the robots, actions to be taken, as well as autonomy of the human in the collaboration (Wang et al., 2019). It is therefore critical in HRC task design to consider LOA modes suitable for the user and applicable to the task (Kaber & Endsley, 1997). Other factors that that could potentially influence the LOA design should also be considered such as the amount of work involved in the task, herein defined as level of workload (Onnasch et al. 2014b; Wickens et al. 2010) and the degree of complicated actions needed to complete the task, herein defined as level of task complexity (Bailey and Scerbo 2007; Crandall and Goodrich 2002).

Workload addresses the actual and perceived amount of work that the human operator experiences which includes the effort invested in the task (Hart and Wickens 1990; Xu et al. 2018). It can generally be described in terms of the elements which constitute the cost of accomplishing the goal for the human operator in the HRC (Hart 2006). These elements could be task-related (such as mental, temporal and physical demands, (Hart & Staveland, 1988)), operator-related (such as skill, strategy, experience, (Hilburn & Jorna, 2001)) or machine-related (such as poorly designed controls, feedback, inappropriate or inadequate automation (Hart & Wickens, 1990)). Workload consequences could be reflected in the stress, fatigue or frustration experienced by the human operator (Hart 2006), depletion of attentional, cognitive or response resources (Hart and Wickens 1990) as well as in performance changes (Yeh and Wickens 1988).

Task complexity depends on properties of the task (objective complexity) and the perception of the human operator (subjective complexity) (Rasmussen, Standal, and Laumann 2015). It can generally be characterized in terms of the stimuli involved in the task for inputs as well as the behavioral requirements the human operator should emit in order to achieve a specific level of performance (Wood 1986a). The elements include the component complexity - number of distinct actions that the human operator must execute or number of informational cues that should be processed (e.g. the number and type of subtasks to be managed, Olsen & Goodrich, 2003); coordinative complexity - nature of relationships between task inputs and task products, the strength of these relationships as well as the sequencing of inputs (e.g. timing, frequency, intensity and location requirements, Campbell, 1988)) and dynamic complexity - changes in the states of the environment (e.g. cause-effect chains, means-ends connections which the human operator should adapt to, Braarud, 2001; Wood, 1986a).

Objective of the study

Previous research identified relations between workload and task complexity in terms of task demand factors contributing to workload as a result of the level of complexity of the task (Wickens et al. 2015). However, there are limited studies that investigated these factors in relation to the design of LOA modes suitable for HRC assembly tasks while operationalizing these LOA modes to support practical use in different collaboration contexts (Kolbeinsson, Lagerstedt, and Lindblom 2019). The current study aims to examine LOA design for different levels of workload (LOW) and different levels of complexity (LOC) for HRC in an assembly task. Since human operators could be stressed while collaborating with the robot on joint tasks (Arai et al., 2010), it is important to take into account user preferences and their perception regarding ease of use. This is in addition to the assessment of the quality of task execution and usability of the system. We design, implement and evaluate LOA modes in a user study involving 80 participants in different workload conditions and task complexities. We hypothesized that specific LOAs will improve users' interaction and enhance their performance in the midst of additional workload of a secondary task at different task complexities. User preferences regarding the LOA modes in the various conditions were assessed subjectively while two constructs were additionally designed for the evaluation: quality of task (QoT) execution and usability.

The model to evaluate the potential interactions of LOA, LOW and LOC with respect to the user preferences, quality of task execution, and usability is presented in section 2. This is followed by the research methods in section 3 which includes description of the system design, LOA modes, task, and experimental evaluations of the design. Section 4 is devoted to the results of the experiments conducted. Conclusions and suggestions for future work are discussed in the last section.

2. Model

Definition of constructs

The model for the study (Figure 1) depicts possible effects of LOA, LOW and LOC on different aspects of the HRC. One of the aspects is the *User preference*, which is operationally used here as the choice of the users regarding the LOA mode that meets their needs and expectations in the collaboration. The other aspects of the HRC were assessed using specially designed constructs (depicted in Figure 1) which are defined as follows:

Quality of task (QoT) execution

The extent to which specific goals in a task are accomplished to a specified degree of accuracy under a specified period of time (ISO 9001 2020). This construct involves accuracy of the executed task, time to complete the task, and the number of stages completed in the secondary task.

Usability

The extent to which the robotic system can be used to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use (ISO 2018). This construct is composed of effectiveness and efficiency including the satisfaction derived from the perceived ease of use.

Figure 16. Constructs for assessments

Hypotheses for the study

Predictions on the influence of LOA, LOW and LOC on these constructs along with the user preference are presented as the study hypotheses with accompanying rationale for each of these hypotheses.

In the design of adjustable robot autonomy in human-robot systems, it was pointed out that as task complexity increases, robot effectiveness is likely to reduce if the robot is operating at higher autonomy (Ashcraft, Goodrich, and Crandall 2019). Users seem to intuitively understand that autonomous systems such as the robot system developed in this study could have difficulties in more complex situations with high uncertainty. Users usually thus prefer to have more control due to higher confidence in their own ability to handle decisions at such higher levels of complexity (Endsley, 1995). We therefore propose:
H1a *- Participants will prefer the low LOA for higher task complexities.*

Research has also shown that as automation increases, workload is expected to decrease, particularly if the automation is properly designed and does not provide new challenges and tasks relating to monitoring or other forms of engagement (Onnasch et al. 2014a). Automation generally provides the opportunity for the user to allocate attention to other concurrent tasks involved in high workload (Hocraffer and Nam 2017; Wickens 2008). Based on this, we propose:
H1b *- Participants will prefer the high LOA for high task workload.*

Several meta-studies conducted regarding levels of automation (Onnasch et al. 2014a; Wickens et al. 2010) seem to suggest that the workload experienced by users is influenced by the LOA of the system, particularly in situations of routine performance. This does not discountenance the effect of task complexity but seems to point to the effect level of workload may have in low task complexity. The preference of participants based on the LOA being utilized is therefore influenced by the level of workload, particularly in low complex task. We, therefore, propose***:***
H1c *- Participants will prefer the high LOA for high workloads at low task complexity*

We assume, based on the aforementioned task complexity demands that high task complexity could involve higher uncertainties and failure. High LOA at high task complexity where more uncertainties can arise may not reduce workload, but rather create additional workload involving users monitoring to ensure performance (Murthy 2007; Niu et al. 2018). We propose therefore,

that participants may prefer to have more control if task complexity increases. This serves as the basis for
H1d *- Participants will prefer the low LOA for higher workloads at high task complexity.*

It has been established in literature that in routine performance, high LOA tends to increase the quality of task execution as related to accuracy, time to complete task and performance of the users (Onnasch et al. 2014a). We suspect that in low complex tasks, where there are lower probabilities of errors, uncertainties and failure, both high and low workloads can be better handled by the users if the automation affords them the opportunity to share their attention to improve performance (Wickens 2008). We therefore propose:
H2 *– Quality of task (QoT) execution will be higher with high LOA when the low complex task is performed at either high or low workload level.*

Several studies involving LOA have revealed the possibility of extending users' capabilities when the level of autonomy of the robot increases (Endsley, 2017). Usability explained previously in terms of the effectiveness, efficiency, and perceived ease of use (Rani et al. 2002), may increase if the system is operated at high LOA. This is also true even in situations of low workload (Davis 1989). We therefore propose:
H3 *- Usability will be higher with high LOA when the low complex task is performed at either low or high workload level.*

The system model depicting the connection between these hypotheses and the study variables are presented in Figure 2.

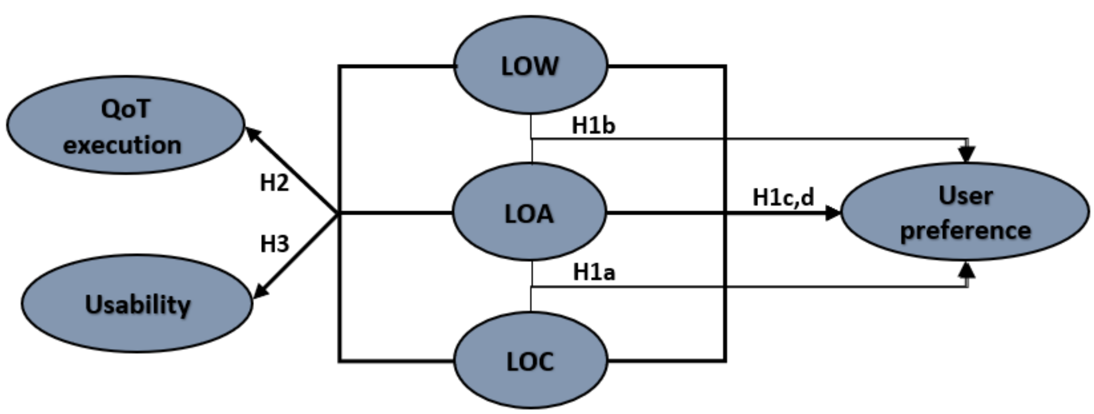


Figure 17. The system model:
LOW,LOA,LOC – levels of workload, automation, complexity; QoT – Quality of task

3. Methods

Overview

The HRC assembly task simulates a work scenario where participants are expected to assemble blocks made from cubes according to a configuration presented to them through a user interface. The robot brings to them a cube at each time. The task was performed in two LOA modes, at different LOW and two different LOC based on the experimental design protocol. Effectiveness and efficiency were assessed under the QoT execution construct while user preferences along with ease of use were added to the assessment of the usability construct.

Experimental system

The experimental system consists of a robotic arm, user interface (presented on a computer), cubes to be assembled and the human operator (Figure 3). The robotic arm is a 4 degree of freedom DOBOT Magician (https://www.dobot.cc/dobot-magician/product-overview.html). It is 135 mm high, 158 mm wide and has a 320 mm radius with a payload of 500 g. It connects to the computer through a USB connection and was equipped with a suction gripper to pick up the cubes.

This robotic arm was programmed for the two LOA modes using the Python programming language. Both modes involved the robot bringing the cubes in a sequence one after another from a predetermined place according to the specific LOA the robot is operating in. The user communicates with the robot through a user interface implemented on a GUI screen (Figure 4). The configuration to be assembled is displayed on the GUI screen when starting the task. The robot releases the cube when it reaches the front of the participant. The participants are expected to assemble the cubes when received from the robot and place these cubes in a marked area on the desk in front of them.

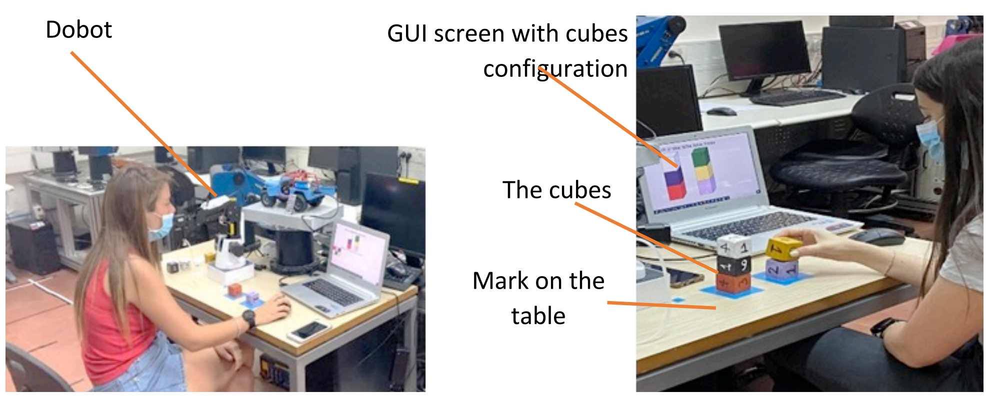


Figure 18. The experimental setup

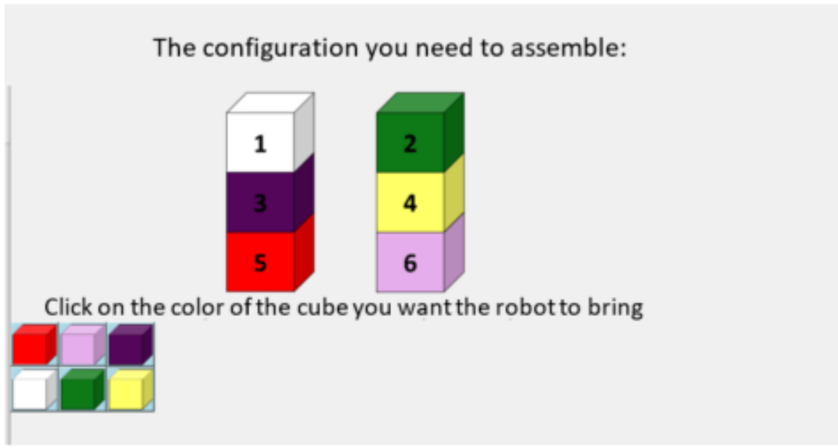


Figure 19. GUI screen

Experimental design

The experimental design includes three independent variables: LOA (two levels), LOW (two levels) and LOC (two levels). A between-within participants experimental design was conducted with the LOA as the within variables while LOW and LOC were the between variables. There are four between participant groups consisting of a combination of the LOW and LOC. Each participant was randomly assigned to one of the four groups where the participant experiences both LOA modes as seen in Table 1. The description of the LOA modes along with the LOW and LOC are provided as follows:

3.1.1. Levels of automation (LOA) modes

Low LOA – The human operator (user) has the autonomy over the type and order of cubes desired. The human operator must identify the type of block needed to fit the required configuration to be assembled per time and then select the required cube through the user interface. The robot supports the user by bringing the type of cube the user selected.

High LOA – The robot has the autonomy to bring the specific type of cube and in the order preprogrammed in its operation. The user does not have to identify a specific type of cube. The user simply demands for a cube through the user interface and the robot brings the type of cube suitable for the specific configuration assembled per time.

3.1.2. Levels of workload (LOW)

Low LOW - The users perform only the main task which consists of assembling cubes to match the specific configuration required. The workload involves some task demands such as the physical demand of arranging the cubes, mental demand of thinking about the type of cube that would match the required configuration and some temporal demand related to completing the task in the shortest possible time.

High LOW – The users carry out the main task (composed of the aforementioned dimensions of workload) along with a secondary task. The secondary task was an off-the shelf well known cognitive game, the "RUSH HOUR" thinking game (Figure 5, https://www.thinkfun.com/products/rush-hour/). It involves arranging toy cars in a way to get a specific car out of a gridlock. There are tabs at each stage showing how to arrange the cars, and afterwards, the player has to find a way to get the required car (red car) out. Once the user has succeeded in getting the red car out, the user proceeds to the next stage and arranges the cars according to what appears on the tab of the next stage. This contributes additional task demands to the overall workload.

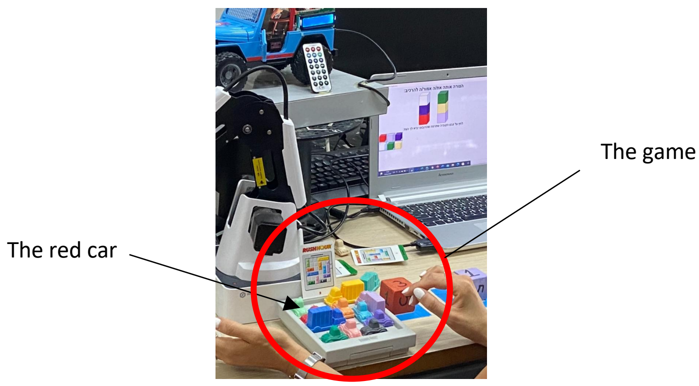
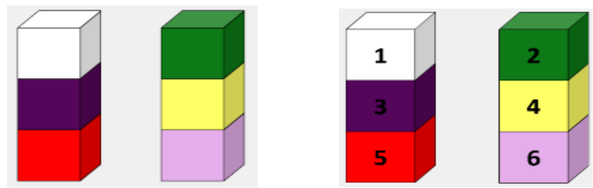


Figure 20. "RUSH HOUR" game

3.1.3. Levels of complexity (LOC)

Low LOC –the cubes for the assembly differ only by color. The users are required to assemble the cubes to match particular configurations characterized by differences in color pattern (Figure 6a). A specific number of cubes must be used to assemble the required configuration while considering the sequence and location of the specific cubes' color of cubes.

High LOC –the cubes for the assembly differ in color and by the numbers on a particular side (Figure 6b). The users are required to assemble the cubes in color patterns as done in the low LOC condition, but in addition, they must ensure that the specific numbers on particular color of cubes match the required configuration per time. The level of complexity is increased by the additional information cue (presence of numbers) and their spatial consideration (position of the number in the configuration).



a b

Figure 21. Sample of cubes configurations in a). Low LOC and b). High LOC

Table 6. Experimental Design

		Level of Workload (LOW)			
		Low LOW		**High LOW**	
		High LOC	**Low LOC**	**High LOC**	**Low LOC**
Level of automation (LOA)	**Low LOA**	Condition 1 – LLH The **user chooses** via a GUI screen which color of cube the robot will bring him. The user concentrates only on the **main task**, **with** reference to the numbers written on the cubes.	Condition 2 – LLL The **user chooses** via a GUI screen which color of cube the robot will bring him. The user concentrates only on the **main task**, **without** reference to the numbers written on the cubes.	Condition 5 – LHH The **user chooses** via a GUI screen which color of cube the robot will bring him. The user concentrates on performing a **main** + **secondary task** simultaneously, **with** reference to the numbers written on the cubes.	Condition 6 – LHL The **user chooses** via a GUI screen which color of cube the robot will bring him. The user concentrates on performing a **main** + **secondary task** simultaneously, **without** reference to the numbers written on the cubes.
	High LOA	Condition 3-HLH The **robot brings** the cubes to the user in a predefined order. The user concentrates only on the **main task**, **with** reference to the	Condition 4-HLL The **robot brings** the cubes to the user in a predefined order. The user concentrates only on the **main task, without** reference to the numbers	Condition 7-HHH The **robot brings** the cubes to the user in a predefined order. The user concentrates on performing a **main** + **secondary task**	Condition 8 – HHL The **robot brings** the cubes to the user in a predefined order. The user concentrates on performing a **main** + **secondary task** simultaneously,

		numbers written on the cubes.	written on the cubes.	simultaneously, **with** reference to the numbers written on the cubes.	**without** reference to the numbers written on the cubes.

Participants

Eighty undergraduate industrial engineering third year students (44 females, 36 males, Mean age=26, SD=1.4) at Ben-Gurion University participated in the study. All students had experience with both computers and robots. Participation was voluntary and every participant received compensation in the form of a bonus point which contributes to a credit in one of their courses.

Experimental Procedure

Participants completed a preliminary questionnaire which was composed of demographics questions for the participants and the Negative Attitudes Towards Robots Scale (NARS, (Syrdal et al. 2009b). NARS questionnaire examines the participants' perception of technology and robots. Then, the participant experienced two experimental trials where they collaborated with the robot in each trial. In each trial, the user collaborated with the robot to assemble the configuration that appeared during the GUI in a specific LOA (high/low) in random order. The robot brings the cubes to the participant in a mode corresponding to the specific LOA in that trial condition. The participant took the cube from the robot each time and placed the cube in the place marked for it, according to the configuration required.

A post-trial questionnaire was completed by the participants after each trial regarding their experience with the robot. The questionnaire was rated on a 5-point Likert scale ranging from "1 – strongly disagree" to " "5 = strongly agree". At the end of the two trials, each participant completed a final questionnaire where they indicated their preferred level of automation.

Dependent Variables

The dependent variables were effectiveness, efficiency and ease of use of the system. These were measured objectively and subjectively as follows and used to form the quality of task and usability constructs using the analyses defined below.

3.1.4. Objective Measures

The objective measures (Table 2) included:

The accuracy of the robot during the task – calculated from the number of times the robot erred in bringing the cubes (e.g., failed to catch a cube, brought an incorrect cube). This was measured in relation to the effectiveness of the system (explained in Table 2).

The total time it took the participant to complete the task for each trial. The time of the trial in which the participant experienced the higher level of automation was constant. This was measured in relation to the efficiency of the system.

The heart rate change of the participant was measured through a Garmin watch at the beginning and end of each iteration (calculated as shown in equation 1). The difference in heart rate indicated the level of ease the participant may be experiencing during the experimental trials (Rani et al. 2002, 2004). This was measured in relation to the ease of use of the system (explained in Table 2).

$$HR\ Change\ = \frac{HR\ after - HR\ before}{HR\ before} \quad (1)$$

Half of the participants experienced the higher LOW and performed a secondary task in addition to the main task. For each participant, the performance in the secondary task was measured according to the stage they reached in the secondary task (the number of stages they pass).

Table 7. Objective Measures

Dependent Variable	Measurement
Effectiveness	Accuracy (number of times the robot erred)
	Performance in the secondary task (number of sub-tasks completed - solved cards) (for the high LOW group)
Efficiency	Time to complete the task (*seconds*)
Ease of use	Heart rate change

3.1.5. Subjective Measures

The subjective measures were collected through questionnaires which were composed of questions regarding the participants' experience with the robot. The post-trial questionnaire and the variables assessed are presented in Table 3. The post-trial questionnaire included NASA-TLX questions (Hart and Staveland 1988) to assess perceived workload in relation to the efficiency of the system. This was measured in this context as the extent of resources demanded in the task. The post-trial questionnaire also included technology acceptance model (TAM) questions to assess perceived ease of use (Davis 1989). The participants indicated their level of agreement on a 5-point Likert scale ranging from "1 = strongly disagree" to "5 = strongly agree". The final questionnaire was designed to assess user preferences regarding LOA modes and to evaluate their perceptions as they collaborate with the robot at specific LOA modes (Table 4).

Table 8. Subjective Measures

Dependent Variable	Measurement	Question
Effectiveness	Accuracy	Did the robot make a mistake during the mission?
	Secondary task	Did the game negatively affect your performance in the main task?
Efficiency	Mental demand	The task was mentally demanding
	Physical demand	The task was physically demanding
	Temporal demand	The pace of the mission made me accelerate my work
	Effort	I had to work hard to finish the task at the level I performed it
	Performance	I was successful in carrying out the task I was asked to do
	Frustration	I felt despair / stress / nerves while performing the task
	Overall perceived workload	Aggregated raw NASA-TLX scores (Hart 2006)
Ease of Use	Easy to use	I think the system is easy to use
	Understanding	It was clear to me what the robot was doing
	Intention to use	I would love to use this system on a daily basis
	Useful	Interacting with the robot can help people who have difficulty moving
	Perceived reliability	Humans can rely on this robot
	Trust	I felt the robot could be trusted
	Satisfaction	Overall, I am satisfied with the way the interaction with the robot in the task was conducted

Table 9. User Preference Questionnaire

1.	Did you feel a difference between the two iterations?

2. If so, what was different?
3. Which of the trials would you prefer?
4. Did you enjoy the task?

Analysis

Each participant performed two trials in the experiment. In both trials, the participant performed the experiment at a specific level of workload and complexity, but in each trial, a different level of automation was experienced in a random order. A t-test was applied to check if there was a significant effect between the iterations. Then, a generalized linear mixed model (GLMM) was applied to analyze the data with the type of LOA, LOW and LOC, with the variances between the participants selected as the random effect. All tests were designed as two-tailed with a significance level of 0.05.

The items in the user preference questionnaire were analyzed individually to assess the preferences and perceptions of the users for each LOA mode they experienced. The variables: *accuracy*, *time to complete the task* and *number of completed sub-tasks* were compounded through principal component analysis (PCA) to form the QoT execution construct assessed in hypothesis H2. This transformed all the constituent variables into a single construct containing only the principal and relevant factors forming the construct. Similarly, the Usability construct to be assessed in hypothesis H3 was a compilation of the following variables through PCA: *effectiveness*, *efficiency,* and *ease of use*.

4. Results

4.1 Participants' Characteristics

4.1.1 NARS - Negative Attitude towards Robots Scale analysis

The NARS results revealed that 21.06% of the participants had a negative attitude towards situations and interactions with robots while 63.65% were neutral about it. 26.58% had highly negative attitudes towards the social influence of robots, 47.61% had a low attitude and 25.81% were neutral about it. 65.82% had a highly negative attitude towards the concept of robots having emotions, 8.87% were indifferent about it while 25.31% had a low negative attitude towards it.

4.2 Evaluation of the Interaction

4.2.1 LOA preference

Most of the participants (59%) preferred the lower LOA, in which they felt more involved and in control of the task however, the difference between the two levels of automation was not significant *(t=-1.365, P=0.174).* Additionally, there was no difference in preferences depending on the order of experiencing the LOA. 57.5% of the participants who experienced first the high LOA and then low LOA, preferred the high LOA (Figure 7, right), compared to 60% of the participants who experienced first the low LOA and then the high LOA that preferred the high LOA (Figure 7, left).

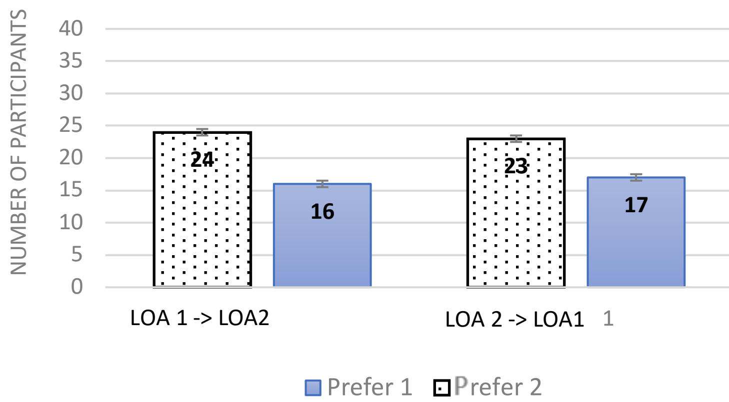


Figure 22. LOA preference depending on the order of experiencing LOA

(each experiment included 40 participants)

The results (Figure 8-9) revealed that:

- 57.5% of the participants that experienced the high LOC preferred the low LOA (in line with H1a).
- 80% of the participants that experienced the high LOW preferred the high LOA (in line with H1b).
- 90% of the participants that experienced the high LOW together with the low LOC preferred the high LOA (in line with H1c).
- 65% of the participants that experienced the high LOW together with the high LOC preferred the high LOA (as opposed to H1d).

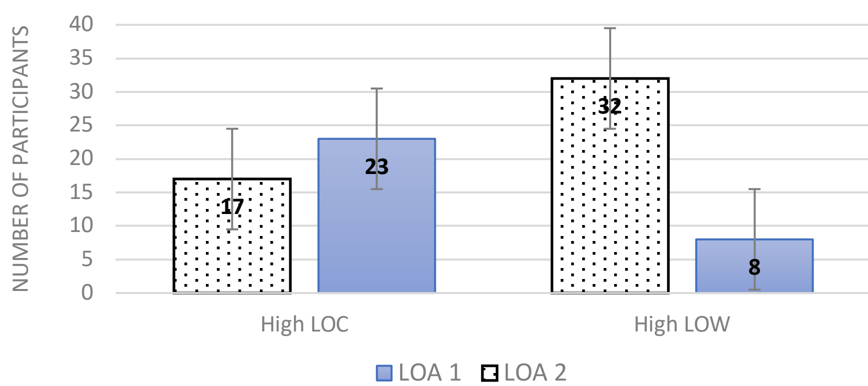


Figure 23. LOA preferences when participants experienced high LOW/LOC

(each experiment included 40 participants)

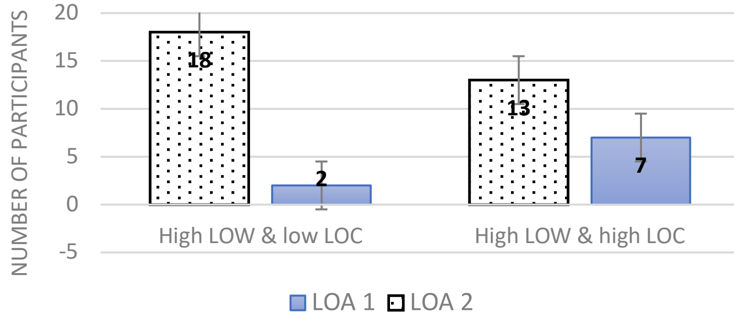


Figure 24. LOA preferences for different combinations of LOW and LOC (each experiment included 20 participants)

4.2.2 Effectiveness

LOW had significant influence on the number of errors the participant perceived (F(1,32)=11.91, P=0.04) and the performance of the secondary task (M=2.35, SD=0.85, F(1,32)= 4.23, P=0.00). All of the participants finish the first stage of the game (Figure 10). The majority reached the second stage of the game while only 10 reached the fourth stage.

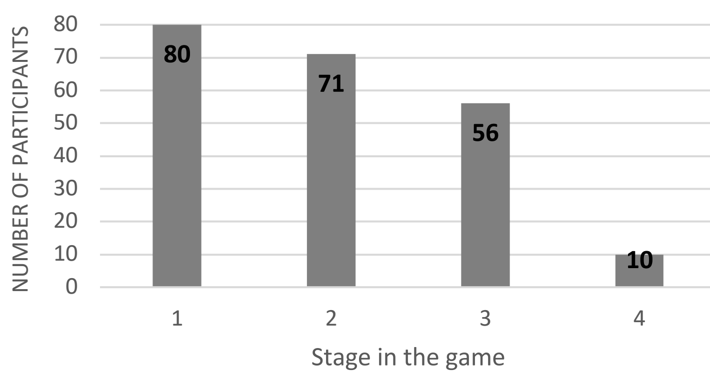


Figure 25. Number of participants who reached stage 1/2/3/4 in the secondary task

4.2.3 Efficiency

Time to complete the task. The three independent variables had significant effect on the completion time: LOA *(F(1,152)=136.82 ,p=0.00)*, LOW *(F(1,152)=5.757, p=0.018)* and LOC *(F(1,152)=6.167,p=0.014)*. At the higher LOA, the time to complete the task was constant and stood at 87.3 seconds. In the lower LOA, as expected, it took more time for the participant to complete the task *(M=108.57, SD=16.39)*. At a higher LOW it took participants longer to complete the task *(M=99.72, SD=19.22)* than at the low level *(M=95.64, SD=10.2)* as expected. Similarly, when the LOC was higher, it took them longer to complete the task *(M=99.87, SD=18.86)* when compared to the low *level (M=95.59, SD=11.11)* (Figure 11).

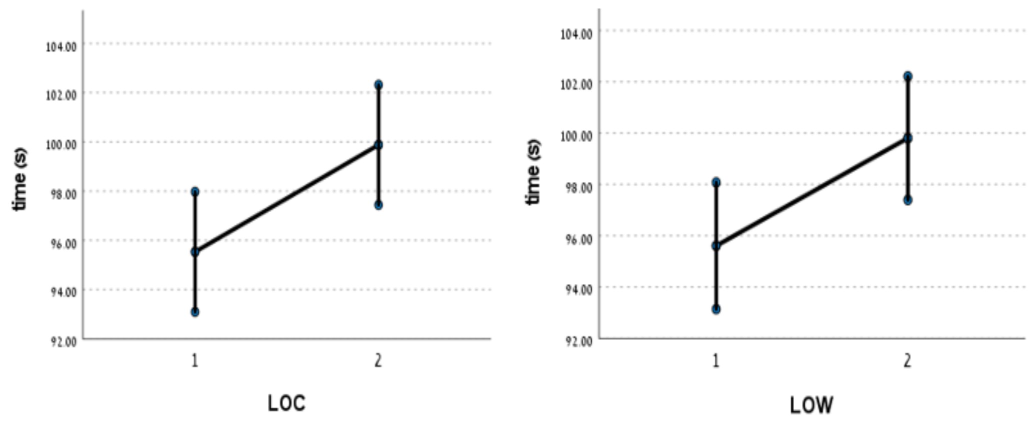


Figure 26: Time to complete the task in LOC (left) and LOW (right)

The combination of LOA with each of the other independent variables had a significant interaction effect, LOA*LOW *(F(1,152)=6.98 ,P=0.009)* and LOA*LOC *(F(1,152)=1.86, P=0.026)* (Figure 12).

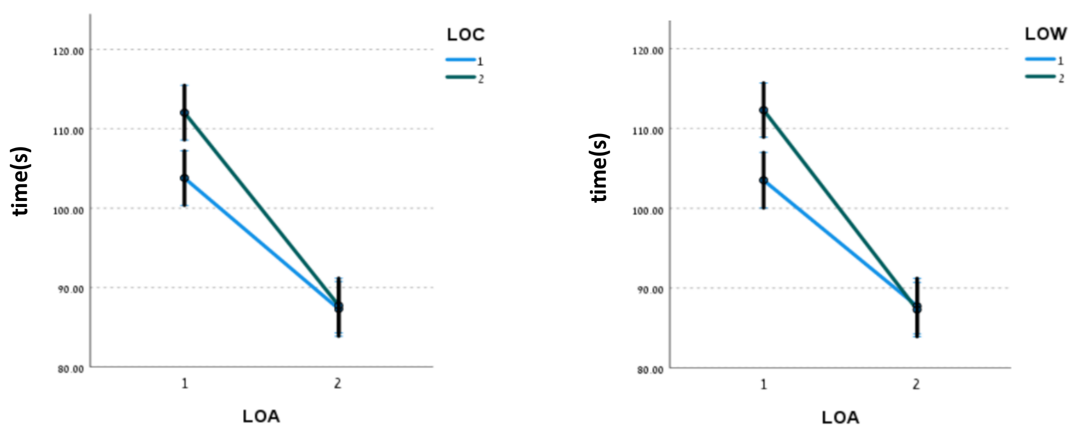


Figure 27: Interaction variable LOA with LOC (left) and LOW (right)

Considering those that performed the higher level of workload, LOA *(P=0.00)* and LOC *(P=0.00)* had also significant effect in this measure *(M=99.72, SD=19.22)*. The interaction variable LOA*LOC *(P=0.00)* also had significant influence (Figure 13).

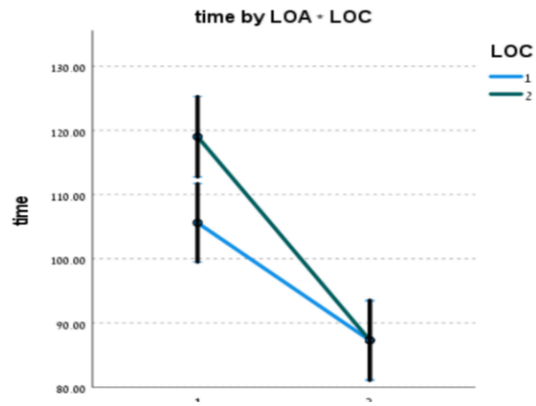


Figure 28. Time to complete the task for those who experienced high LOW

LOW had significant effect in many of the measures: mental *(M=1.88, SD=1.11, F(1,152)=38.42, P=0.00)*, temporal *(M=1.37, SD=0.66, F(1,152)=29.54, P=0.00)*, performance *(M=2.45, SD=1.37, F(1,152)=41.35, P=0.00)*, effort (*M=1.99, SD=1.17, F(1,152)=39.93, P=0.00)* and frustration *(M=1.68, SD=0.98, F(1,152)=19.62, P=0.00)*.

As shown in Figure 14, at the high level of workload, the mental load *(M=2.39, SD=1.18)*, the temporal *(M=3.15, SD=1.22*), the effort *(M=2.59, SD=1.19)* and the frustration *(M=2.09, SD=1.09)* the participants felt was higher than at the lower level [mental *(M=1.32, SD=0.71, P=0.00),* temporal *(M=1.67, SD=1.11, P=0.00),* effort *(M=1.35, SD=0.75, P=0.00)* and frustration *(M=1.25, SD=0.61, P=0.00)*]. This is as compared to the performance *(M=4.49, SD=0.65)* that was better in the lower LOW *(M=3.35, SD=1.09)*.

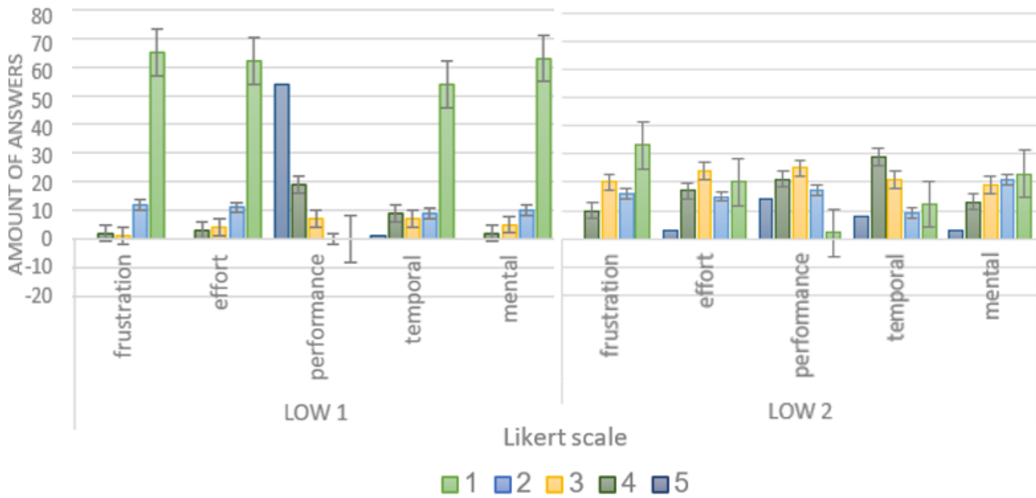


Figure 29. Outcome of perceived workload assessement

In terms of the perceived effort, the interaction variable between LOA and LOC also was significant *(F(1,32)=3.18, P=0.02)*. When LOA was high and LOC was low the participants testified that they felt the least effort *(M=1.82, SD=1.15)*.

LOA significantly influenced *perceived workload* as measured through the aggregated raw NASA-TLX scores *(F(1,152)=32.1, P=0.04)*. At the low level of automation, the participants experience greater load *(M=11.56, SD=0.9)*, than at the higher level *(M=11.2, SD=1.09)*.

4.2.4 Ease of Use

Heart rate change. The heart rate at the beginning of each iteration *(M=80.7, SD=15.83)* was significantly lower than the heart rate at the end of iteration *(M=87.29, SD=16.17)* as expected with significant influence of both LOA *(M=6.39, SD=11.8), (F(1,152)=2.43, P=0.03)* and LOW *(F(1,152)=35.86, P=0.00)*. Higher LOA *(M=8.04, SD=11.42)* and higher LOW *(M=11.64, 11.61)* led to higher change in the heart rate (Figure 15).

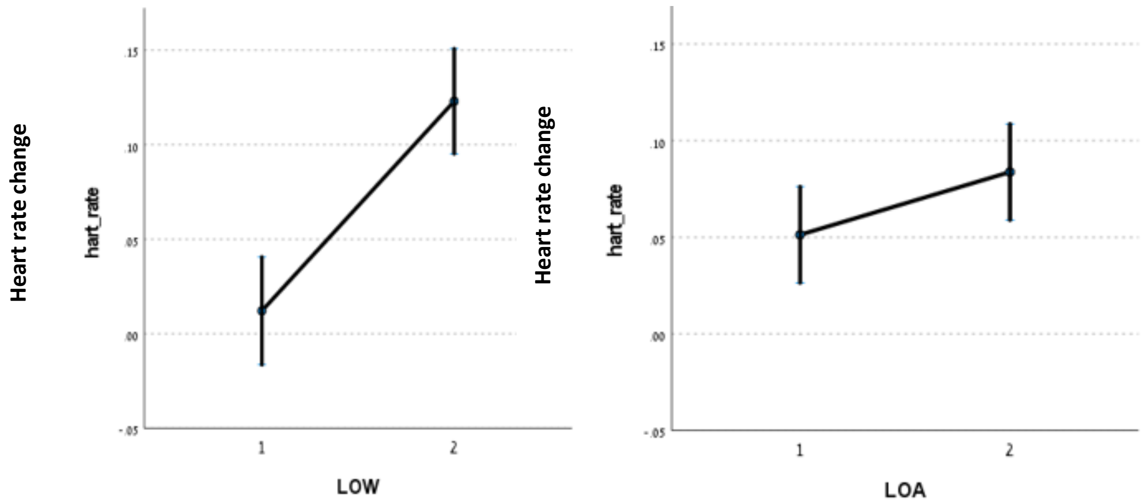


Figure 30. The heart rate change in LOA and LOW

Perceived reliability. LOW had significant effect *(M=4.44, SD=0.73, F(1,152)=5.06, P=0.03)* on perceived reliability as assessed through the questionnaire. The reliability was perceived as higher by the participants who experienced the low LOW *(M=4.55, SD=0.66)* than at the high LOW *(M=4.34, SD=0.61)* as shown in Figure 16.

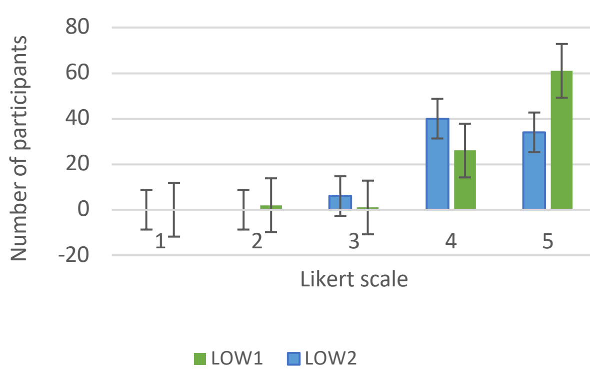


Figure 31. Perceived reliability of the system

Secondary task. LOW had significant influence on the perception of the difficulty of the secondary task *(F(1,32)=59.77, P=0.00)* (Figure 17).

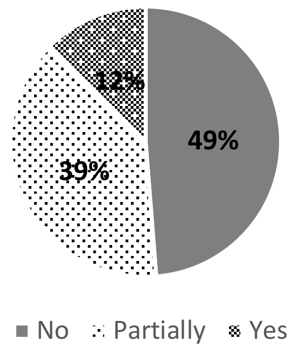


Figure 32. Did the secondary task make it harder for you?

4.2.5 QoT execution

Both LOA (*F(1,152)=4.639,p=0.033*) and LOW (*F(1,152)=93.6,p=0.00*) had significant effect on the QoT execution. The QoT execution was higher at the high LOA when the LOW was low (Figure 18) confirming H2. The higher QoT at a high LOA is consistent with the preferences of the participants.

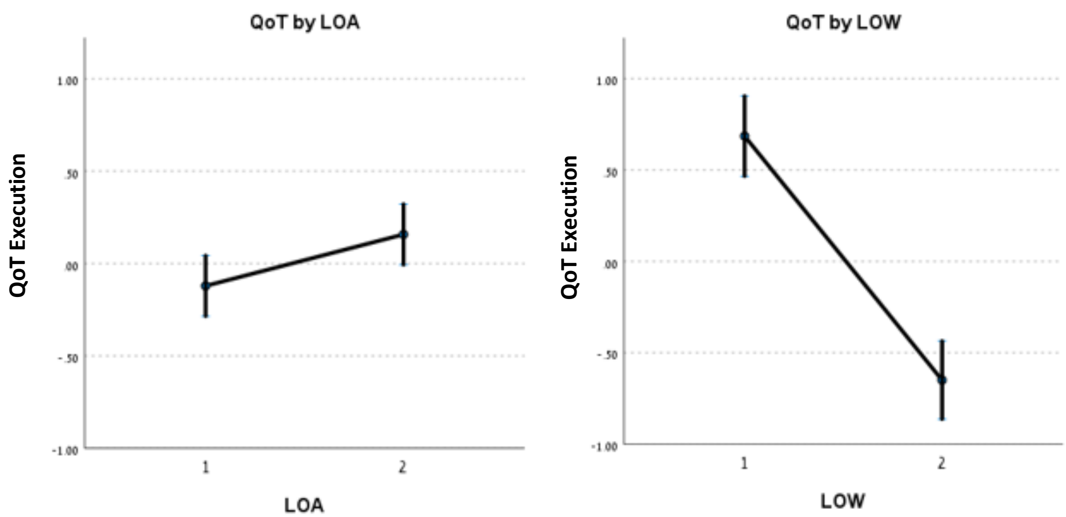


Figure 33: QoT execution for LOA and LOW

4.2.6 Usability

The LOW had significant effect *(F(1,152)=68.935, P=0.00) on usability*. *At* the high LOW, when the participants performed a secondary task in addition to the main task the usability was higher (Figure 19).

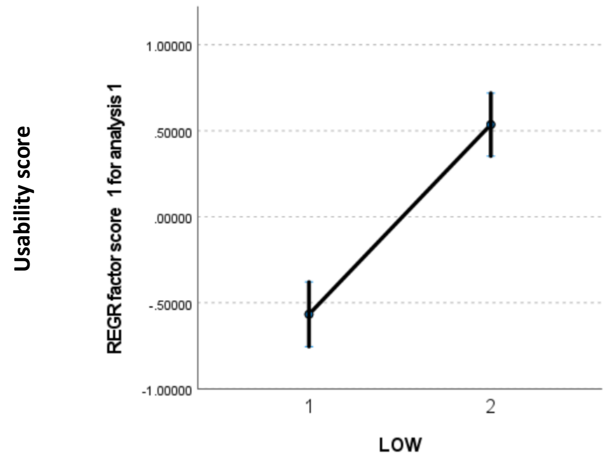


Figure 34. LOW for usability

4.2.7 Summary

A summary of all the variables (with their measures) where significant effects of the independent variables were observed are provided in Table 5 as follows:

Table 10. Summary of significant variables

Dependent Variable	Measurement	Independent Variable	Significance level
Effectiveness *(Objective)*	Performance in secondary task	LOW	0.00
Efficiency *(Objective)*	Time	LOA	0.00
		LOW	0.018
		LOC	0.014
		LOA*LOW	0.009
		LOA*LOC	0.026
Ease of use *(Objective)*	Heart rate change	LOA	0.03
		LOW	0.00
Effectiveness *(Subjective)*	Accuracy	LOW	0.04
	Difficulty of secondary task	LOW	0.00
Efficiency *(Subjective)*	Mental	LOW	0.00
	Temporal	LOW	0.00
	Effort	LOW	0.00

		LOA*LOC	0.02
	Performance	LOW	0.00
	Frustration	LOW	0.00
	Perceived workload	LOW	0.04
Ease of Use	Understanding	LOC	0.05
(Subjective)	Perceived reliability	LOW	0.03

5. Discussion

The results revealed the main influences and interacting influences of LOA, LOW and LOC in the HRC assembly task context. The implications of the influence of these independent variables in relation to the main dependent variables (user perception, quality of task execution and usability) are discussed below.

Influence of LOA

Most participants seem to prefer a low LOA when the task complexity is high. This is in line with H1a, and also in agreement with previous studies where it was stated that a higher LOA may not give a positive outcome in situations where uncertainties, and higher probabilities of failure exist (Onnasch et al. 2014a; Wickens et al. 2010). In high complex tasks where high component and coordinative complexity increases the probabilities of failure (Campbell 1988; Wood 1986b), humans usually have a higher potential to better manage unknown or unexpected situations compared to the robot in the collaboration (Monostori et al., 2006; Wang et al., 2017). This is also seen in the results relating to the perceived performance where lower LOA is rated by the participants to produce higher performance when the task complexity is higher. In higher workload situations, however, where additional resources are needed to complete the task in the least possible time and with minimal effort, higher LOA is preferred (in line with H1b, H1c). The QoT execution and usability were influenced in line with *H2* and *H3* respectively. This reinforces the significance of evaluating LOA modes alongside different workload and complexity situations. There was no significant effect of the order in which participants experienced the LOA modes which highlights the importance of appropriate selection of LOA applicable to different situations. This is important because the LOA design influences human activity, behaviour and involvement in the collaboration and can impose new coordination demands on the human operator (Parasuraman, Sheridan, and Wickens 2000). In our study, the low LOA was designed and implemented in such a way as to ensure that the user's involvement in the task is maintained, and the robot’s involvement lowers the workload. The high LOA seemed to support the user better when the workload increases as seen in the results for usability measures. This points to the necessity of having selectable and adaptable LOA settings in HRC designs to cater for situations of varying secondary tasks demands (Endsley & Kiris, 1995). In such contexts, the robot can be adapted to make additional attentional resources available for the human to handle simultaneous tasks (Kaber & Endsley, 2004).

Workload considerations

LOW had significant influence on most of the measures indicating that the experimental design successfully simulated differences in workload. This inspired further examination of the impact of LOA and LOC for scenarios where the workload was higher (where the participants performed a secondary task in addition to the main task). The interaction between LOA and LOC had significant influence in those workload scenarios. The workload also had significant effect on effectiveness and efficiency of the system leading to reduced QoT execution in situations where the workload was high. This is consistent with the literature highlighting the contribution of task-related demands (such as mental, temporal and physical demands involved in the HRC task) to workload, which could negatively influence resources available to complete task at hand (Hart and Wickens 1990). However, it is also observed that usability (which included the user perception regarding ease of use) increased at higher workload. This reflects the possible stress or fatigue that the users may have experienced at with increased work demands (as seen in the heart rate change results, Figure 14), and the tendency to desire the support of the robot in such workload situations as correlated in (Heger and Singh 2006). Provision is therefore made for workload changes and considerations through LOA options available to improve the QoT execution and usability as desired by the user.

Task complexity considerations

LOC in the current study did not have influence on most of the dependent variables. This may be due to insufficient depiction of the level of complexity in the experimental design leading to minimal influence and perception of the difference between the complexity levels by the participants for the specific users. However, some of the dependent measures where the complexity was significant brings into prominence the relevance of the complexity of the task, the influence on effectiveness, efficiency and ease use. It could also inform the design and selection of LOA modes applicable for the complexity level of each task. The results reveal that both objective and subjective complexity considerations as noted in (Rasmussen, Standal, and Laumann 2015) should be put in view while considering the suitable LOA modes for such HRC assembly tasks. This consequently affects the QoT execution and usability of the system.

Design recommendations and limitations

The study revealed the influence of LOA in the midst of different workload levels and task complexity differences. The results obtained in this study is with respect to the specific task, robot and scenario featured in the study. Furthermore, the evaluation was carried out with users who had experience with computers and robots. There may be significant differences in the influence of these variables when observed in other settings, with different forms of robots and tasks. We expect the results to be amplified with non- technological users. However, the outcome of our study spotlights some key points which could be relevant to other human-robot collaboration setups involving LOA at different task complexities and workload levels. We propose some of these points as design recommendations with caution that additional tests using other platforms may be beneficial.

We propose, based on the outcome of the study that **a lower LOA is recommended for high task complexities** where failure performance may occur, or uncertainties are prominent as noted in (Onnasch et al. 2014b). However, **when the workload is high, a higher LOA could reduce the stress or pressure of additional secondary tasks which the robot could support in**. This was observed in the outcome of the user preferences which tended towards higher LOA when the workload was high. This also agrees with the observations of (Wickens et al. 2010) in their meta-analyses considering the influence of LOA on workload. High LOA, when designed effectively, helps to extend the capabilities of the user to attend to other tasks concurrently as noted by (Endsley & Kiris, 1995). In addition, the influence of the independent variables on the composed constructs (QoT execution and usability) reveals the potential and sensitivity of these constructs for assessment purposes in other HRC tasks.

6. Conclusions and future work

This paper presented the design and evaluation of LOA modes at different workload and task complexity levels for an HRC assembly task. The user study yielded valuable insights into participants' preferences and characteristics of the operator interface related to LOA, LOW and LOC that are required to enhance the user experience and performance. Two constructs were specially designed for this evaluation: quality of task (QoT) execution and usability. Though, the three-way interaction of LOA, LOC and LOW did not influence QoT execution and usability as expected, there were significant two-way interactions across some of the variables assessed. The effect of the interaction of LOA and LOW was particularly significant on the system efficiency. The interaction effect of LOA and LOC was similarly significant as well. This highlights the need to consider the task complexity and workload experienced by the participant when designing LOA for similar human-robot collaboration tasks.

There were main influences of the independent variables across all the variables with the workload playing a major role in the interaction and the human experience during the task. The users' attitudes towards the workload informed some design recommendations regarding the need to ensure that users are always aware of the actions carried out by the robot in all LOA modes. This tends to reduce the stress of the human operators associated with workload shifting to quality control and performance monitoring. 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.

Future work should include improving the design to depict more clearly, the complexity levels of the task for users to perceive. Workload differences with secondary tasks were more evident in the results obtained. Though, other forms of secondary tasks could also be tested with the same robot or other platforms as well. For instance, running the study with a mobile robot for daily tasks that require a wider range of motion may provide additional validation of the study outcomes. Additionally, similar research should be performed for other kind of tasks and types of users. Ongoing research is aimed at performing studies with older adults for some tasks of daily living.

The change of preferences and the differences in the reaction of the older adults should be examined. This is very relevant considering the situation along the COVID-19 pandemic in which many older adults are quarantined at home for long periods. Such assistive robots could be beneficial in performing various tasks for them with different LOA options for different task complexities and workload levels.

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Chapter 6. Discussion and conclusions

This research examined the influence of levels of automation (LOA) in interaction between assistive robots and non-technological users, focusing on older adults. Creating a successful interaction is a pretty challenging task (Breazeal et al. 2016). To achieve this the systems design utilizes levels of automation (LOA) to define the degree to which the robot would perform particular functions in its defined role of assisting the user in a specific task (Parasuraman, Sheridan, and Wickens 2008). The aim is to ensure high quality collaboration between the older adult and the robot in accomplishing desired tasks, without undermining the autonomy, preferences and satisfaction of the older adult. This LOA-aided design seeks a balance between assisting the older adults as much as possible and involving them in the task to avoid idleness, sedentariness, boredom or loss of skill in the long run.

This research revisited the study of automation levels in everyday tasks such as table setting, specific for the older adult population. In this study we focused on several significant aspects in combination with LOA that are important in designing a robot-human collaboration. In addition, the combination of LOA with each of the other variables we examined at each stage of the study.

The first aspect we studied was **LOT**. Existing studies reveal that the information presented to the users significantly influences their comprehension of the robot's behavior, performance and limitations (Chen et al. 2014; Dzindolet et al. 2003; Lyons 2013). This information facilitates the users' knowledge of the automation connected to the task (Endsley 2017b). This affects the users' understanding of their role and that of the robot in any given interaction (Chen et al. 2014; Doranet et al. 2017; Hellström et al. 2018; Lyons 2013). In this study **where the level of involvement of the participant varies with the LOA, it is noteworthy that the LOT preferred is influenced by the LOA the robot is operating in**. *Participants seem to prefer less information (low LOT) when the robot was operating more autonomously (high LOA). They also seem to prefer more information (high LOT) when they were more active with the robot such as the case in low LOA mode*. This agrees with the findings in (Chen et al. 2018) where differences were not found in the transparency level that included only status information and reason without LOA involved. As expected, there was a **tradeoff regarding degree of involvement and time to complete task i.e., at a higher degree of user involvement, more time was spent to complete the task.**

The second aspect investigated was the **feedback** type that the robot gives the user during the task. The feedback loop is also an important feature of interactive systems; it provides the user with information improving the nature of the interaction between a person and a dynamic system. Since older adults' perceptual capabilities and limitations differ from the younger population due to age-related perceptual declines, particularly evident in processing information (Mitzner et al. 2015). Thus, the correct choice of interaction between the assisting environment and the user is of high importance (Broekens et al. 2009). Older adults' interaction with robots requires effective feedback to keep them aware of the state of the interaction for optimum interaction quality (Beer et al. 2014). Results revealed that the **integration of different types of**

feedback during the task increases the participant's involvement, especially at a high level of automation. For the more, it was found that GUI screen feedback for this task is less relevant for adults and they rarely looked at the screen because they were concentrated in the robot. Therefore, it is recommended to focus more on other types of feedback. Furthermore, possibly due to the robot being new to them and therefore demanding more focus, after a certain period of time they will become accustomed to it and prefer visual feedback like a GUI screen.

The additional aspects we addressed in this thesis were levels of workload and complexity of the task, **LOW** and **LOC**. Workload addresses the actual and perceived amount of work that the human operator experiences which includes the effort invested in the task (Hart et al. 1990). Task complexity depends on properties of the task (objective complexity) and the perception of the human operator (subjective complexity) (Rasmussen et al. 2015). It can generally be characterized in terms of the stimuli involved in the task for inputs as well as the behavioral requirements the human operator should emit in order to achieve a specific level of performance (Wood 1986a). Results revealed that the effect of the interaction of LOA and LOW was particularly significant on the system efficiency. The interaction effect of LOA and LOC was similarly significant as well. This highlights the need to **consider the task complexity and workload experienced by the participant when designing LOA for similar human-robot collaboration tasks**. There were main influences of the independent variables across all the variables with the workload playing a major role in the interaction and the human experience during the task. The users' attitudes towards the workload inform some design recommendations regarding the need to ensure that users are always aware of the actions carried out by the robot in all LOA modes.

As expected, from all the studies it emerged that the levels of automation influenced interaction and performance aspects and there seems to be a significant difference in the quality of the interaction at the different levels of automation. A main conclusion refers to the users' preferences for the level of automation in which they perform a joint task with a robot. According to these studies, in the older adults population a preference will be biased to a level that incorporates their involvement in task control while the robot performs the action. In situations where a secondary task is performed during the main task, the preference tendency will be for a higher level of automation. But it is important to mention that the population with which it was tested was students and therefore this study should be advanced with older adults population.

This study yielded valuable insights into participants' preferences and characteristics of the operator interface related to LOA, LOT, feedback, LOW and LOC that are required to enhance the user experience and performance. The robotic systems were designed to assist in a routine task in the home environment.

However, it is important to note that these experiments examined specific scenarios and robotic tasks. In order to generalize these conclusions, additional experiments must be performed to examine different tasks at different levels of workload and complexity.

Another aspect for further research relates to the improving the design to depict more clearly, the complexity levels of the task for users to perceive. Workload differences with secondary tasks

were more evident in the results obtained. Though, other forms of secondary tasks could also be tested with the same robot or other platforms as well.
As stated above, in light of the circumstances of the Corona, the last study was modified and adapted to a target audience of students instead of the older adult population. In the future, as we expand this experiment to our target population, changes will be made to the design of the experiment to accommodate for this. The changes will include changing the task itself, changing the level of the complexity and changing the secondary task to a less thoughtful task. If the changes are made in a tailored manner, I expect to get similar results in the older adult population. I expect when the adults feel the higher workload, they will prefer a higher level of automation, as well as when they experience a higher level of complexity.

In general, this study has limitations that require longitudinal research in order to examine all the effects and reach more stable conclusions.
This research can be applied in the future using a portable and easy-to-operate robotic arm that will converge on adult homes and help them perform, along with them, their daily tasks. Presumably this will bring with it large financial costs but it is important to remember that the potential population giving help to assisting adults is declining while the adult population is increasing. Therefore, the benefit in this case is very high and worth investing into since in the long run it can even be financially rewarding in addition to the profit and benefits it provides to the adults.
With the advance of technology, its decreasing costs and the increasing demand for assistive technology we expect robots to penetrate into many applications. This research provides general recommendations for designing assistive robots for older adults by taking into account the effect of levels of automation as related to levels of transparency, feedback, workload and task complexity.

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List of Appendices

Appendix A- study 2

A.1 BGU ethical committee

I. General

Name of Research Project: Level of automation in combine system human-robot
To which agency is the proposal being submitted (or has been submitted): None.

Principal Investigator/s (or academic supervisor/s):
Name: Vardit Sarne-Fleischmann Name: Yael Edan
Department: IE&M Department: IE&M
Academic position: Phd Academic position: Prof University Telephone:
University Telephone:
Mobile Phone: Mobile Phone:
University Email: varditf@gmail.com University Email: yael@bgu.ac.il
Other Email:
Other Email:

Name(s) of those conducting the research (if different from above):
Name: Dana Gutman Name:
Department: IE&M Department:
Academic position: Academic position:
University Telephone: University Telephone:
Mobile Phone: 0526566525 Mobile Phone:
Email: danagut@post.bgu.ac.il Email:

II. Consent to Participate

Are the subjects able to legally consent to participate in the research? ☒Yes / ☐No
If you answered 'No' to question 1, complete section IIb
Will the subjects be asked to sign a consent form? ☒Yes / ☐No
If you answered 'No' to question 2, explain here:

IIb: Subjects who cannot legally consent (minors, mentally incapacitated, etc.):
Will the subject's legal guardian be asked to sign a consent form? ☐ Yes / ☐ No
If you answered 'No', to question 3, please explain here:
Will the subject be asked to give oral consent? ☐ ☐
Yes / No
Are the instructions appropriate to the subjects' level of understanding? ☐ ☐
Yes / No
Comments: In the case of minors - they will be asked to give oral consent, whereas their parents will be asked to sign a consent form.

6. If informed consent forms will be signed, how will the informed consent forms be stored to ensure confidentiality? All signed forms will be saved in a locked cabinet.

III. Discomfort:

Will the participants be subjected to physical discomfort? ☐ ☒ Yes /
No
Will the participants be subjected to psychological discomfort?: ☐ ☒ Yes /
No
If you answered 'Yes' to question 7 or 8, add here a detailed explanation of the circumstances:

IV. Deception

Does the research involve deceiving the subjects? ☐ Yes / ☒ No
Is the decision on the part of the subject to participate in the study based on deception?
(For example, if they are informed of their participation only after the event.) ☐ Yes / ☒ No
If you answered 'Yes' to question 9 or 10, add here a detailed explanation why deception is necessary:

V. Feedback to the Subject

Note: Although feedback to the subject is recommended for *all* studies, it is required for studies that involve discomfort or deception. Feedback entails providing the subject, upon completion of the experiment, explanation of the experiment and its aims.
Will the subjects be provided with post-experiment oral feedback? ☐ ☒ Yes /
No
Will the subjects be provided with post-experiment written feedback? ☐ ☒ Yes /
No
If you answered 'No' to both questions 11 and 12, explain here: The purpose of the experiment is to find out the optimal level of automation for a simple task, such as table editing for an older population. This goal requires analysis and therefore participants do not receive feedback after the experiment

VI. Compensation for Participation

13. Will the subjects receive compensation for participation? ☒ Yes / ☐
No

Detail here the type and amount of compensation: 50 NIS
If you answered 'No' to question 13, explain the basis for participation:

VII. Privacy:

Will audio and/or visual recordings be made of the subjects? ☒ Yes / ☐ No a. If yes, are they informed of this fact in the informed consent form? ☒ Yes / ☐ No
Will the data collected (apart from the informed consent form) contain identifying details about the subjects? ☒ Yes / ☐ No
a. If the data contains identifying details, please answer here: (1) What steps will you take to ensure the confidentiality of the information? (2) How will the data be stored? (3) What will be done with identifying information or recordings of the subjects at the end of the research?
the data will be encoded and will be deleted after the research

VIII. Withdrawal from the Study:

Will subjects be informed that they may withdraw from the study at any time? ☒ Yes / ☐ No
Will the subjects' compensation for participation be affected if they withdraw from the study before its completion? ☐ Yes / ☒ No a. If yes, are they informed of this fact in the informed consent form? ☐ Yes / ☐ No

IX. Research Equipment

18. Does the research entail the use of equipment other than standard equipment, such as computers, video recording equipment? ☒ Yes / ☐ No 19. If yes, does the equipment being used meet safety standard for use with human subjects? ☒ Yes / ☐ No

Please specify which standards (include documentation where appropriate): During the experiment, hands can be placed in the robot's work area. In order to deal with this situation, we defined clear and defined areas for the individual where he is allowed to work. Morover, the robot which will be used in the study is programmed to avoid collision and to slow down when approaching any obstacle. It meets the ISO 10218-1:2011 safety standard.

Signatories:

Signature: Date: 4.2.19 Name: Yael Edan

Name: Dana Gutman   Position:

A.2 Explanation form for the subject

טופס הסבר לנבדק

<u>נושא המחקר: סוגי משוב במערכת משלבת אדם -רובוט</u>

*גוף השאלון מנוסח בלשון זכר מטעמי נוחות והינו מכוון לשני המינים.

מטרת העל בפרויקט הינה בחינת השפעת סוגי משובים שונים במשימה משותפת בין אוכלוסייה מבוגרת לזרוע רובוטית.

השלב הנוכחי של המחקר והניסוי שיתבצע נערך בבניין 16 במתחם אוניברסיטת בן גוריון בבאר שבע. המחקר עוסק **<u>באפיון המשוב במערכת משלבת אדם -רובוט</u>**. משך המחקר כ-שעה.

במסגרת המחקר תידרש לבצע אינטראקציה עם זרוע רובוטית במשימת עריכת שולחן.

הזרוע הרובוטית אמורה לסייע לך במשימה ולכן נסה להתנהג בצורה טבעית ורגילה כפי שאתה נוהג לתקשר עם אדם אחר בחיי היומיום. בנוסף, חשוב לנו להדגיש כי הזרוע מגיבה למגע ותוכנתה כך שתספיק לפעול אם היא מזהה סכנה ולכן אין צורך לחשוש מהפעולה המשותפת

הניסוי הנוכחי מתחלק לשלושה חלקים. החלק הראשון מורכב ממספר שאלונים אישיותיים, החלק השני מורכב מביצוע משימת עריכת השולחן. חלק זה יתבצע שלוש פעמים כך שבכל פעם תקבל משוב שונה מהרובוט על פעולתו . בסיום כל פעם יש לענות על שאלון קצר בנוגע לאינטראקציה עם הרובוט.

בסוף המחקר תידרשו לענות על שאלון מסכם.

לא מתבצעת שמירה של הפרטים המזהים של הנבדקים. כל נבדק מקבל מספר נבדק אשר מופרד מפרטי הנבדק. כל השאלונים יימסרו בתום המחקר לחוקרת הראשית הממונה על המחקר וישמרו באחריותה.

אם מכל סיבה שהיא הנך חש שלא בנוח, בבקשה עצור את הניסוי ועורך הניסויים ייגש אליך באופן מיידי. בכל עת ובכל שלב תוכל, אם תרצה, להפסיק את השתתפותך במחקר. במידה ורצונך כי הניסוי ייפסק, תשוחרר מהניסוי ללא התחייבות.

A.3 Consent form for the subject

טופס הסכמה לנבדק

נושא המחקר: סוגי משוב במערכת משלבת אדם <u>ורובוט נייד</u>

נבדק יקר,
בבקשה קרא את דף ההסבר באשר לניסוי. במידה ויש שאלות, נשמח לענות.
בבקשה וודא כי הנך מבין היטב את שלבי המחקר.

להזכירך, המחקר עוסק באפיון המשוב במערכת משלבת אדם -רובוט. במהלך הניסוי תדרש לבצע מספר משימות אשר דורשות אינטראקציה עם הרובוט שבמהלכן הרובוט ישלח לך משובים בהתאם לשלב במשימה ובהתאם לפקודות שתעביר לו. משך הניסוי לכל היותר שעה.
באוניברסיטת בן גוריון בבאר שבע .16הניסוי מתקיים בבניין

אני החתום מטה:*

שם פרטי ומשפחה:	ת.ז.
חתימה:	טלפון:

א. מצהיר/ה בזאת כי אני מסכים/ה להשתתף בניסוי, כמפורט במסמך המפרט את חלקי הניסוי.
ב. מצהיר שהוסברו לי בפירוט כל חלקי הניסויי והסכמתי ליטול בו חלק לאחר שנענו כל שאלותיי לגבי כל אחד מחלקי הניסוי .
ג. מצהיר בזאת כי הוסבר לי על-ידי החוקרת: <u>*נעה מרקפלד*</u>

1. כי אני חופשי לבחור שלא להשתתף בניסוי וכי אני חופשי להפסיק בכל עת את השתתפותי בניסוי מכל סיבה שהיא .
2. במידה ואני חש ברע או באי נוחות במהלך הניסוי חובה עלי לדווח לנסיין על מנת להפסיק את הניסוי.
3. מובטח שזהותי האישית תשמר סודית על-ידי כל העוסקים והמעורבים במחקר ולא תפורסם בכל פרסום כולל בפרסומים מדעיים.
4. מובטחת לי נכונות לענות לשאלות שיועלו על-ידי .

יתכן ובמהלך הניסוי החוקרים יצלמו תמונות וסרטונים לצורכי מחקר בלבד.
במידה ואתה מאשר\ת זאת, חתום כאן:_______________

במידה ואת\ה מסכימים שתמונתכם תופיע בפרסומים שונים שיוצגו לציבור אנא ציינו :
☐ אני מסכים שתמונתי תופיע בפרסומים שונים
☐ איני מעוניין שתמונתי תופיע

*הצהרה זו הנה סודית ואינה ניתנת להעברה או שימוש לצורך שום דבר או גורם אחר פרט לצורכי מחקר זה.

תאריך ___________________ חתימת מעביר הניסוי________________

אנו מודים לך על השתתפותך במחקר.

A.4 Dermographique quaternaires

Participant's number *

Short answer text

(age) גיל *

Short answer text

(gender) מגדר *

- ◯ זכר
- ◯ נקבה

A.5 TAP Questionnaire

:אנא ציין באיזו תדירות אתה משתמש \ מבצע כל אחד מהדברים הבאים

0 : אף פעם
1 : פעם בחצי שנה עד שנה
2 : פעם בחודשיים עד 5 חודשים
3 : פעם בחודש
4 : 1-3 פעמים בשבוע
5 : כמעט כל יום

1. טכנולוגיה נותנת לי יותר שליטה בחיי היומיום שלי *
2. טכנולוגיות חדשות הופכות את החיים שלי לקלים יותר *
3. אני יכול ללמוד להשתמש במוצרי ושירותי היי-טק חדשים ללא עזרה מאחרים *
4. אני נהנה ללמוד להשתמש בטכנולוגיות חדשות *
5. טכנולוגיה שולטת בחיי יותר ממה שאני שולט בטכנולוגיה *

A.6 NARS Questionnaire

אנא ציין את מידת הסכמתך עם האמירות הבאות (NARS:)
1 - מאוד לא מסכים
2 - לא מסכים
3 - נייטרלי
4 - מסכים
5 - מסכים מאוד

1. הייתי מרגיש נינוח לדבר עם רובוטים
*
2. הייתי מרגיש בנוח אם היה ניתן לי תפקיד בו הייתי צריך להשתמש ברובוטים
*
3. הרעיון שרובוטים יפעילו שיקול דעת לגבי דברים מלהיב אותי
*
4. עצם העמידה מול רובוט מלחיצה אותי
*
5. אני מרגיש שאם אהיה תלוי ברובוטים יותר מידי, משהו רע עלול לקרות
*

A.7 Post-trial questionnaire

אנא ציין את מידת הסכמתך עם האמירות הבאות:

1- מאד לא מסכים
2- לא מסכים
3- נטריילי
4- מסכים
5- מסכים מאד

1. ההתנסות עם הרובוט הלחיצה אותי *

	1	2	3	4	5	
מאוד לא מסכים	○	○	○	○	○	מסכים מאד

2. הרגשתי נוח בדרך התקשורת שלי עם הרובוט *

	1	2	3	4	5	
מאוד לא מסכים	○	○	○	○	○	מסכים מאד

3. כמה מאמץ היית צריך/ה להשקיע בעת ביצוע המשימה *

	1	2	3	4	5	
מאמץ רב מאד	○	○	○	○	○	מאמץ קל מאד

4. הרגשתי ערני במהלך העבודה עם הרובוט *

	1	2	3	4	5	
מאוד לא מסכים	○	○	○	○	○	מסכים מאד

5. הייתי מרוצה מחלוקת העבודה ביני ובין הרובוט *

	1	2	3	4	5	
מאוד לא מסכים	○	○	○	○	○	מסכים מאד

6. במהלך הניסוי הרגשתי שאני יכול לסמוך על הרובוט *

	1	2	3	4	5	
מאוד לא מסכים	○	○	○	○	○	מסכים מאד

7. הרובוט שגה במהלך ביצוע המשימה *

	1	2	3	4	5	
מאוד לא מסכים	○	○	○	○	○	מסכים מאד

A.8 Final questionnaire

1. חשתי בהבדל בין ההרצות השונות (בין החזרות) *

- כן
- לא
- לא יודע

2. במידה וחשת בהבדל בין התרחישים השונים, מה לדעתך היו ההבדלים ?

טקסט של תשובה ארוכה

3. באיזו הרצה חלוקת העבודה בינך לבין הרובוט הייתה הטובה ביותר? *

- בראשונה
- בשניה
- בשלישית
- באף אחת מהן
- בכולן בצורה שווה
- אחר...

4. באיזו מידה תהי/ה מעונינ/ת להיעזר ברובוט במשימה זו, במידה ותדרש/י לפנות שולחן כל יום במהלך השבוע?

	1	2	3	4	5	
מאד לא מסכים	○	○	○	○	○	מסכים מאד

Appendix B- study 3

B.1 BGU ethical committee

Application for Approval to Use Humans as Subjects in Empirical Study

I. General

Name of Research Project: Level of automationand workload in combine system human-robot To which agency is the proposal being submitted (or has been submitted): None.

Principal Investigator/s (or academic supervisor/s):	
Name: **Vardit Sarne-Fleischmann**	**Name**: **Yael Edan**
Department: IE&M	**Department:** IE&M
Academic position: Phd	**Academic position: Prof**
University Telephone:	**University Telephone**:
Mobile Phone:	**Mobile Phone:**
University Email: varditf@gmail.com	**University Email:** yael@bgu.ac.il
Other Email:	**Other Email:**

Name(s) of those conducting the research (if different from above):	
Name: Dana Gutman	**Name**:
Department: IE&M	**Department:**
Academic position: Master student	**Academic position:**
University Telephone:	**University Telephone**:
Mobile Phone:	**Mobile Phone:**
Email: danagut@post.bgu.ac.il	**Email:**

II. Consent to Participate

Are the subjects able to legally consent to participate in the research? ☒ Yes / ☐ No

If you answered 'No' to question 1, complete section IIb

Will the subjects be asked to sign a consent form? ☒ Yes / ☐ No

If you answered 'No' to question 2, explain here**:**

IIb: Subjects who cannot legally consent (minors, mentally incapacitated, etc.):
Will the subject's legal guardian be asked to sign a consent form? Yes / No
If you answered 'No', to question 3, please explain here:
Will the subject be asked to give oral consent? ☐ ☐
Yes / No
Are the instructions appropriate to the subjects' level of understanding? ☐ ☐
Yes / No
Comments: In the case of minors - they will be asked to give oral consent, whereas their parents will be asked to sign a consent form.

If informed consent forms will be signed, how will the informed consent forms be stored to ensure confidentiality? All signed forms will be saved in a locked cabinet.

III. Discomfort:
Will the participants be subjected to physical discomfort? ☐ ☒ Yes / No
Will the participants be subjected to psychological discomfort?: ☐ ☒ Yes / No
If you answered 'Yes' to question 7 or 8, add here a detailed explanation of the circumstances:

IV. Deception
Does the research involve deceiving the subjects? ☐ Yes / ☒ No
Is the decision on the part of the subject to participate in the study based on deception?
(For example, if they are informed of their participation only after the event.) ☐ ☒ Yes / No
If you answered 'Yes' to question 9 or 10, add here a detailed explanation why deception is necessary:

V. Feedback to the Subject
Note: Although feedback to the subject is recommended for *all* studies, it is required for studies that involve discomfort or deception. Feedback entails providing the subject, upon completion of the experiment, explanation of the experiment and its aims.
Will the subjects be provided with post-experiment oral feedback? ☐ ☒ Yes / No
Will the subjects be provided with post-experiment written feedback? ☐ ☒ Yes / No
If you answered 'No' to both questions 11 and 12, explain here: The purpose of the experiment is to find out the optimal level of automation for a simple task, such as table editing for an older population. This goal requires analysis and therefore participants do not receive feedback after the experiment

VI. Compensation for Participation
13. Will the subjects receive compensation for participation? ☐ ☒ Yes / No

Detail here the type and amount of compensation: -
If you answered 'No' to question 13, explain the basis for participation: Students in Automation course will receive 1 bonus point to their grade.

VII. Privacy:

Will audio and/or visual recordings be made of the subjects? Yes / No ☒ ☐ a. If yes, are they informed of this fact in the informed consent form? Yes / No ☒ ☐
Will the data collected (apart from the informed consent form) contain identifying details about the subjects? ☒ ☐ Yes / No
a. If the data contains identifying details, please answer here: (1) What steps will you take to ensure the confidentiality of the information? (2) How will the data be stored? (3) What will be done with identifying information or recordings of the subjects at the end of the research?
the data will be encoded and will be deleted after the research

VIII. Withdrawal from the Study:

Will subjects be informed that they may withdraw from the study at any time? ☒ ☐ Yes / No
Will the subjects' compensation for participation be affected if they withdraw from the study before its completion? Yes / No ☐ ☒ a. If yes, are they informed of this fact in the informed consent form? Yes / No ☐ ☐

IX. Research Equipment

18. Does the research entail the use of equipment other than standard equipment, such as computers, video recording equipment? ☒ ☐ Yes / No

19. If yes, does the equipment being used meet safety standard for use with human subjects?

☒ Yes / ☐ No

Please specify which standards (include documentation where appropriate): The robot which will be used in the study (Dobot) is programmed to avoid collision and to slow down when aproaching any obstacle. It meets the ISO 10218-1:2011 safety standard.

Signatories:

Name: Dana Gutman **Position**:

Signature: **Date**: 4/6/20

Name: Yael Edan **Position**:

Signature: **Date**: 4.6.20

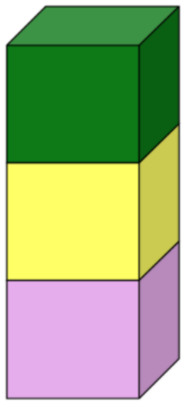
B.2 Explanation form for the subject

נבדק יקר,

המחקר עוסק באינטראקציה במערכת משלבת אדם -רובוט.

אתה תבצע את הניסוי **פעמיים**.

במהלך כל הרצה תידרש להרכיב מגדל קוביות צבעוניות בסדר מסוים. ברגע שתבחר להתחיל את המשימה יופיע לך על מסך המחשב הצורה אותה עליך להרכיב בשיתוף עם הרובוט. לדוגמא ------------->



עליך להבין תוך כדי תנועה כיצד שיתוף הפעולה יעבוד ביניכם.

ברגע שהרובוט מביא לך את הקובייה עליך לתפוס אותה ברגע שהרובוט ישחרר אותה.

את המגדל עליך לבנות במיקום לפי הסימון שמוצג על השולחן.

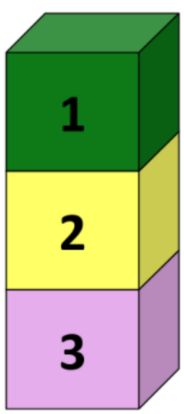
כעת יהיה עליך לענות על שאלון מקדים ולמלא את מספר המשתתף שלך כי שמופיע בקובץ דוקס.
לאחר כל הרצה של הניסוי תמלא שאלון אמצע ולסיום תמלא שאלון סוף.
זמן הניסוי: 15 דק'.

נבדק יקר,

המחקר עוסק באינטראקציה במערכת משלבת אדם -רובוט.

אתה תבצע את הניסוי **פעמיים**.

במהלך כל הרצה תידרש להרכיב מגדל קוביות צבעוניות בסדר מסוים ובנוסף לשים לב למספרים שמופיעים על כל קובייה. ברגע שתבחר להתחיל את המשימה יופיע לך על מסך המחשב הצורה אותה עליך להרכיב (צבע + מספר) בשיתוף עם הרובוט. לדוגמא ------------->



עליך להבין תוך כדי תנועה כיצד שיתוף הפעולה יעבוד ביניכם.

ברגע שהרובוט מביא לך את הקובייה עליך לתפוס אותה ברגע שהרובוט ישחרר אותה.

את המגדל עליך לבנות במיקום לפי הסימון שמוצג על השולחן.

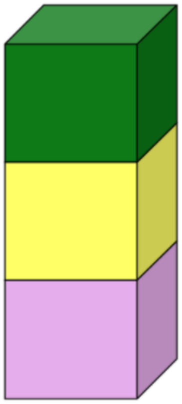
כעת יהיה עליך לענות על שאלון מקדים ולמלא את מספר המשתתף שלך כי שמופיע בקובץ דוקס.
לאחר כל הרצה של הניסוי תמלא שאלון אמצע ולסיום תמלא שאלון סוף.
זמן הניסוי: 15 דק'.

נבדק יקר,

המחקר עוסק באינטראקציה במערכת משלבת אדם -רובוט.

אתה תבצע את הניסוי **פעמיים**.

במהלך כל הרצה תידרש להרכיב מגדל קוביות צבעוניות בסדר מסוים. ברגע שתבחר להתחיל את המשימה יופיע לך על מסך המחשב הצורה אותה עליך להרכיב בשיתוף עם הרובוט. לדוגמא -------------<



תוך כדי המשימה עליך יהיה לשחק את המשחק "שעת שיא" כאשר המטרה שלך לסיים את הניסוי ולהגיע לשלב הכי גבוה שתספיק. (אם אינך מכיר את המשחק, פנה אלינו שנסביר לך).

עליך להבין תוך כדי תנועה כיצד שיתוף הפעולה יעבוד ביניכם.

ברגע שהרובוט מביא לך את הקובייה עליך לתפוס אותה ברגע שהרובוט ישחרר אותה.

את המגדל עליך לבנות במיקום לפי הסימון שמוצג על השולחן.

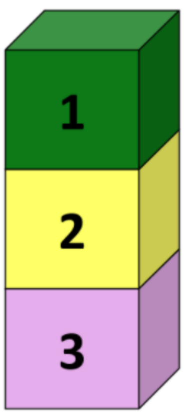
כעת יהיה עליך לענות על שאלון מקדים ולמלא את מספר המשתתף שלך כי שמופיע בקובץ דוקס.
לאחר כל הרצה של הניסוי תמלא שאלון אמצע ולסיום תמלא שאלון סוף.
זמן הניסוי: 15 דק'.

נבדק יקר,

המחקר עוסק באינטראקציה במערכת משלבת אדם -רובוט.

אתה תבצע את הניסוי **פעמיים**.

במהלך כל הרצה תידרש להרכיב מגדל קוביות צבעוניות בסדר מסוים ובנוסף לשים לב למספרים שמופיעים על כל קובייה. ברגע שתבחר להתחיל את המשימה יופיע לך על מסך המחשב הצורה אותה עליך להרכיב (צבע + מספר) בשיתוף עם הרובוט. לדוגמא -------------<



תוך כדי המשימה עליך יהיה לשחק את המשחק "שעת שיא" כאשר המטרה שלך לסיים את הניסוי ולהגיע לשלב הכי גבוה שתספיק. (אם אינך מכיר את המשחק, פנה אלינו שנסביר לך).

עליך להבין תוך כדי תנועה כיצד שיתוף הפעולה יעבוד ביניכם.

ברגע שהרובוט מביא לך את הקובייה עליך לתפוס אותה ברגע שהרובוט ישחרר אותה.

את המגדל עליך לבנות במיקום לפי הסימון שמוצג על השולחן.

כעת יהיה עליך לענות על שאלון מקדים ולמלא את מספר המשתתף שלך כי שמופיע בקובץ דוקס.
לאחר כל הרצה של הניסוי תמלא שאלון אמצע ולסיום תמלא שאלון סוף.
זמן הניסוי: 15 דק'.

B.3 Consent form for the subject

נבדק יקר,

ההסבר של הניסוי. במידה ויש שאלות, נשמח לענות בבקשה קרא את דף.

בבקשה וודא כי הנך מבין היטב את שלבי המחקר.

להזכירך, המחקר עוסק באינטראקציה במערכת משלבת אדם -רובוט. במהלך הניסוי תידרש להרכיב מגדל קוביות בשיתוף פעולה עם הרובוט. אתה תוכל בכל רגע נתון להגיד לרובוט לעצור והוא יעצור.

משך הניסוי לכל היותר חצי שעה.

הניסוי מתקיים בבניין 16 באוניברסיטת בן גוריון בבאר שבע.

.

אני החתום מטה*:

ת.ז. שם פרטי ומשפחה:

טלפון: חתימה:

1. מצהיר/ה בזאת כי אני מסכים/ה להשתתף בניסוי, כמפורט במסמך המפרט את חלקי הניסוי.
2. מצהיר שהוסברו לי בפירוט כל חלקי הניסויי והסכמתי ליטול בו חלק לאחר שנענו כל שאלותיי לגבי כל אחד מחלקי הניסוי.
3. מצהיר בזאת כי הוסבר לי על-ידי החוקרת: דנה גוטמן

1) כי אני חופשי לבחור שלא להשתתף בניסוי וכי אני חופשי להפסיק בכל עת את השתתפותי בניסוי מכל סיבה שהיא.

2) במידה ואני חש ברע או באי נוחות במהלך הניסוי חובה עלי לדווח לנסיין על מנת להפסיק את הניסוי.

3) מובטח שזהותי האישית תשמר סודית על-ידי כל העוסקים והמעורבים במחקר ולא תפורסם בכל פרסום כולל בפרסומים מדעיים.

4) מובטחת לי נכונות לענות לשאלות שיועלו על-ידי.

5) יתכן ובמהלך הניסוי החוקרים יצלמו תמונות וסרטונים לצורכי מחקר בלבד. במידה ואתה מאשר\ת זאת, חתום כאן:_______________

במידה ואת\ה מסכימים שתמונתכם תופיע בפרסומים שונים שיוצגו לציבור אנא ציינו.

אני מסכים שתמונתי תופיע בפרסומים שונים ☐

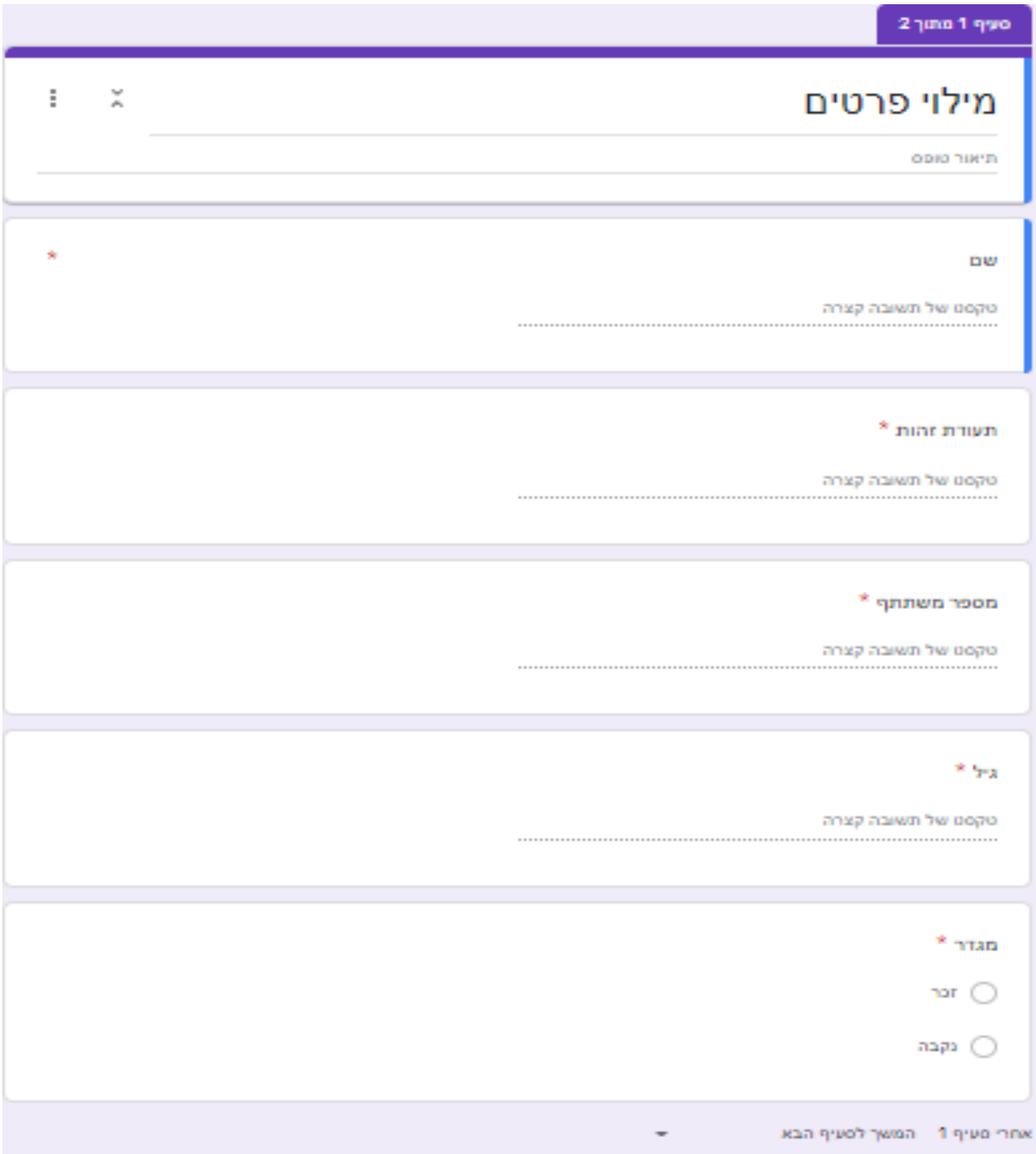
איני מעוניין שתמונתי תופיע ☐

* הצהרה זו הנה סודית ואינה ניתנת להעברה או שימוש לצורך שום דבר או גורם אחר פרט לצורכי מחקר זה.

_______________ תאריך ___________________ חתימת מעביר הניסוי

אנו מודים לך על השתתפותך במחקר.

B.4 Pre-questionnaires


סעיף 1 מתוך 2

מילוי פרטים

תיאור טופס

שם *

טקסט של תשובה קצרה

תעודת זהות *

טקסט של תשובה קצרה

מספר משתתף *

טקסט של תשובה קצרה

גיל *

טקסט של תשובה קצרה

מגדר *

- זכר
- נקבה

אחרי סעיף 1 המשך לסעיף הבא

סעיף 2 מתוך 2

שאלון מקדים

תיאור (אופציונלי)

אנא ציין את מידת הסכמתך עם האמירות הבאות (NARS):

1 - מאוד לא מסכים
2 - לא מסכים
3 - ניטרלי
4 - מסכים
5 - מסכים מאוד

מספר משתתף *

טקסט של תשובה קצרה

הייתי מרגיש לא בנוח אם היה ניתן לי תפקיד בו הייתי צריך להשתמש ברובוטים *

1 ○ 2 ○ 3 ○ 4 ○ 5 ○

אני חושב שרובוטים ומערכות אינטליגנציות מלאכותיות לא צריכים להפעיל שיקול דעת לגבי דברים *

1 ○ 2 ○ 3 ○ 4 ○ 5 ○

הייתי מרגיש במתח רק מלעמוד לפני רובוט *

1 ○ 2 ○ 3 ○ 4 ○ 5 ○

אני מרגיש שאם אהיה תלוי ברובוטים יותר מידי יהיו לכך השלכות שליליות *

1 ○ 2 ○ 3 ○ 4 ○ 5 ○

כיצד היית מגדיר את הרמה שלך במשחקי הרכבה *

נמוכה מאוד 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ גבוהה מאוד

שאלון Big Five inventory

אני רואה את עצמי כ:

1 - מאוד לא מסכים
2 - לא מסכים
3 - ניטרלי
4 - מסכים
5 - מסכים מאוד

1. עד כמה אתה פתוח לרעיונות וחוויות חדשות? *

	1	2	3	4	5	
מאוד לא מסכים	○	○	○	○	○	מסכים מאוד

2. בעת ביצוע משימה, עד כמה חדור מטרה אתה? *

	1	2	3	4	5	
מאוד לא מסכים	○	○	○	○	○	מסכים מאוד

3. עד כמה אתה מופעל על ידי העולם החיצון? *

	1	2	3	4	5	
מאוד לא מסכים	○	○	○	○	○	מסכים מאוד

4. עד עמה אתה שם את צורכי האחר לפני הצרכים שלך? *

	1	2	3	4	5	
מאוד לא מסכים	○	○	○	○	○	מסכים מאוד

5. עד כמה אתה מושפע מלחץ ומחווית כישלון? *

	1	2	3	4	5	
מאוד לא מסכים	○	○	○	○	○	מסכים מאוד

B.5 Post- trial questionnaire

שאלון אמצע

מה מידת הסכמתך עם האמירות הבאות ביחס לאינטראקציה עם הרובוט
1 - מאוד לא מסכים
2 - לא מסכים
3 - נייטרלי
4 - מסכים
5 - מסכים מאוד

השאלון מנוסח בלשון זכר אך פונה לשני המינים

מספר משתתף *

טקסט של תשובה קצרה

הרצה מספר *

○ 1
○ 2

מה הדופק שמראה השעון? *

טקסט של תשובה קצרה

האינטראקציה עם הרובוט יכולה לסייע לאנשים המתקשים בתנועה *

1	2	3	4	5
○	○	○	○	○

הרגשתי שניתן לסמוך על הרובוט *

1	2	3	4	5
○	○	○	○	○

בני אדם יכולים לתת אמון ברובוט זה *

1	2	3	4	5
○	○	○	○	○

באופן כללי אני מרוצה מהדרך שבה התנהלה האינטראקציה עם הרובוט במשימה *

1	2	3	4	5
○	○	○	○	○

המשימה הייתה תובענית מבחינה מנטלית *

1	2	3	4	5
○	○	○	○	○

המשימה הייתה תובענית מבחינה פיזית *

1	2	3	4	5
○	○	○	○	○

קצב המשימה גרם לי להאיץ את עבודתי *

1	2	3	4	5
○	○	○	○	○

הייתי מוצלח בביצוע המשימה שהתבקשתי לעשות *

1	2	3	4	5
○	○	○	○	○

הייתי צריך לעבוד קשה בכדי לסיים המשימה ברמה בה ביצעתי אותה *

1	2	3	4	5
○	○	○	○	○

הרגשתי ייאוש/לחץ/עצבים במהלך ביצוע המשימה *

1	2	3	4	5
○	○	○	○	○

אשמח להשתמש במערכת הזאת ביום יום *

○ כן

○ לא

אני חושב שהמערכת קלה לשימוש *

○ כן

○ לא

היה לי ברור מה הרובוט עשה *

1	2	3	4	5
○	○	○	○	○

האם הרובוט שגה במהלך המשימה

○ כן

○ לא

האם המשחק העמיס עליך לבצע את המשימה?

○ כן

○ לא

○ חלקית

○ לא היה משחק

לאיזה שלב הגעת במשחק? (אם לא היה משחק אל תענה)

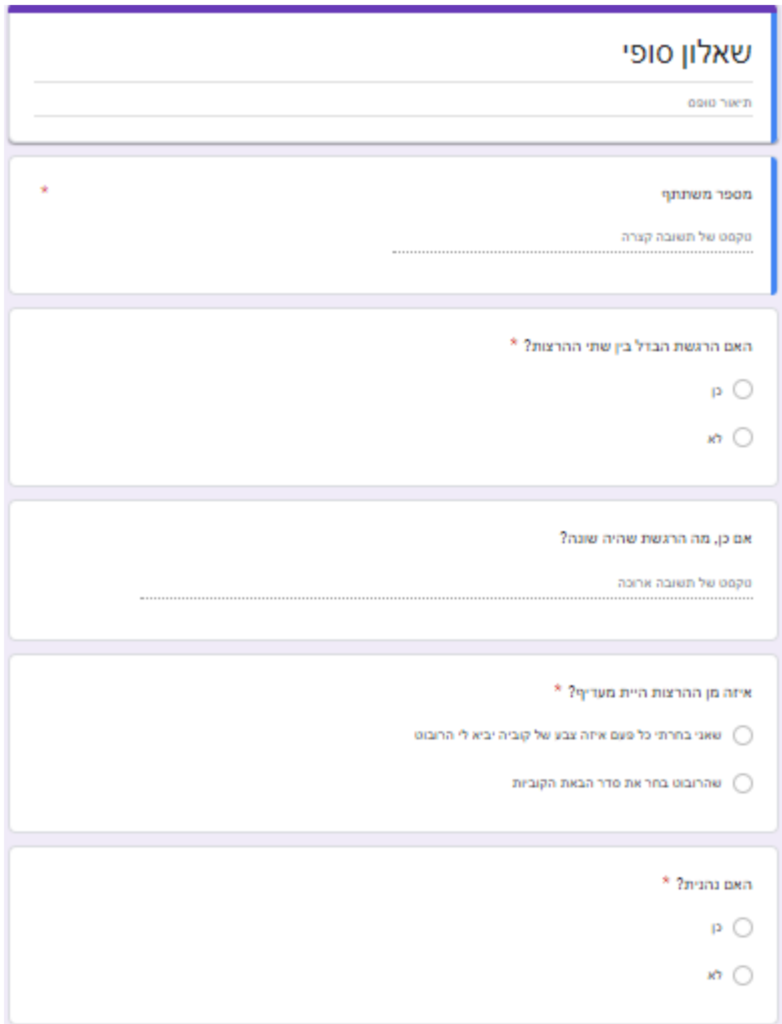
טקסט של תשובה קצרה

האם אתה שגית במהלך המשימה

○ כן

○ לא

B.6 Final questionnaire


שאלון סופי

תיאור טופס

מספר משתתף *

טקסט של תשובה קצרה

האם הרגשת הבדל בין שתי ההרצות? *

כן

לא

אם כן, מה הרגשת שהיה שונה?

טקסט של תשובה ארוכה

איזה מן ההרצות היית מעדיף? *

שאני בחרתי כל פעם איזה צבע של קוביה יביא לי הרובוט

שהרובוט בחר את סדר הבאת הקוביות

האם נהנית? *

כן

לא

אוניברסיטת בן גוריון בנגב

הפקולטה למדעי ההנדסה

המחלקה להנדסת תעשייה וניהול

רמות אוטומציה של רובוט במשימת סיוע לאוכלוסיית הגיל השלישי

מאת: דנה גוטמן

מנחה/ים: פרופ' יעל אידן

חתימת המחבר: ____________ תאריך: 03.01.2020

אישור המנחה: ____________ תאריך: 03.01.2020

אישור יו"ר ועדת תואר שני מחלקתית: ____________ תאריך: ____________

ינואר 2020

אוניברסיטת בן גוריון בנגב

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ינואר 2020