Eye-tracking-Driven Shared Control for Robotic Arms: Wizard of Oz Studies to Assess Design Choices

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Advances in eye-tracking control for assistive robotic arms provide intuitive interaction opportunities for people with physical disabilities. Shared control has gained interest in recent years by improving user satisfaction through partial automation of robot control. We present an eye-tracking-guided shared control design based on insights from state-of-the-art literature. A Wizard of Oz setup was used in which automation was simulated by an experimenter to evaluate the concept without requiring full implementation. This approach allowed for rapid exploration of user needs and expectations to inform future iterations. Two studies were conducted to assess user experience, identify design challenges, and find improvements to ensure usability and accessibility. The first study involved people with disabilities by providing a survey, and the second study used the Wizard of Oz design in person to gain technical insights, leading to a comprehensive picture of findings.

CCS Concepts: • **Human-centered computing** → **Accessibility systems and tools**; *Pointing devices*; *Empirical studies in accessibility*; • **Software and its engineering** → Development frameworks and environments.

Additional Key Words and Phrases: Assistive Robotics, Eye-Tracking, Robot Manipulation, Assistive Device, User Experience, Disability, Wizard of Oz

1 Introduction

People with physical disabilities such as locked-in syndrome, cerebral palsy, late-stage amyotrophic lateral sclerosis, or multiple sclerosis benefit from non-haptic controls such as Brain-Computer Interfaces and eye-tracking controllers. Implementation as control inputs for assistive robotic arms can enhance user independence, self-determination, and privacy in daily life by reducing the dependency on family members and caregivers [3, 4, 17].

Regardless of the controlled technology, challenges have been identified with such input devices in the areas of safety, availability of participants for clinical trials, privacy, interdisciplinarity, and cost [17, 32, 35, 44]. This has led to the development of a variety of robot control methods that differ in terms of input modalities and control strategies [17, 33]. Depending on the input modality, the achievable varying level of robot autonomy yields different advantages and disadvantages. For instance, direct control of the robot leads to the need for mode switches to cover the 3-dimensional space the robot can move, or to control all the joints of the robot, enhancing the needed concentration on the tasks [17, 23, 31]. The implementation of a shared control approach, in which tasks are partially automated, has been demonstrated to effectively address this issue. Such approaches have been shown to positively impact interaction perception and reduce the time required to complete tasks [6, 31]. A potential challenge associated with a high level of automation is user discomfort, which can arise if users feel that they are losing control over the system. In this context, community feedback is essential to improve design and evaluate usability and accessibility [4, 34, 41]. It provides firsthand insights into user expectations and perceptions of their daily lives, thus enhancing acceptance rates [11, 34].

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This work incorporates feedback from the community on an initial shared control design to identify challenges and improve the design. A Wizard of Oz design of the eye-tracking-driven control was developed, with which two studies were conducted. The first study was an online survey distributed to people with disabilities, their family members and friends, and caregivers. The objective was to assess the usability in daily life and to identify the tasks that participants would prefer to perform. The stakeholder group was defined as individuals with physical disabilities who are unable to use their extremities to control the robot. In the second study, non-disabled participants with varying levels of robotics experience interacted with the system to obtain technical parameters that would provide constraints for a future control algorithm. In this context technical parameters describe for example the maximum and minimum dwell time and the level of accuracy needed for a robust control. The main contributions of this work are as follows:

(1) Presentation of a shared control design for everyday tasks.
(2) An evaluation of functionality and usability through opinions of potential users, their families, caregivers and non-disabled participants.
(3) Improvements in the initial shared control design gained from the studies.

2 Background

2.1 Shared control for robotic arms

"Shared control in assistive robotics blends human autonomy with computer assistance, thus simplifying complex tasks for individuals with physical impairments" [20]. Advances in sensing, inference, modeling, and learning methods have lead to novel developments in the research area [39]. In this context, researchers are investigating impact factors on shared control. Literature has been reviewed to find such factors influencing human-robot-interaction. three categories were introduced to facilitate the overview over the found outcomes: Field of use, technical challenges, level of autonomy, and user individuality and preferences.

The *field of use* establishes the boundaries within which shared controls are to be utilized. Robots can be used for daily tasks in unstructured environments [42], household chores [24], and personal tasks such as personal hygiene or medical procedures [47]. This determines the positioning of the robot, whether it must be attached to an electric wheelchair, on the bedside, or on a table [42], and leads to the initial setup configuration and limitation in robot choice.

The *technical challenges* include **reliability and functionality** of the system: Safety, robustness and success rate in e.g. task completion is a standard that has to be ensured [42, 47] and the requirements are defined in ISO 13482 [19]. The system must be robust to changing or unorganized environments, especially when the robot is mounted on an electric wheelchair [39, 42]. The system should be **easy to learn and use**, which also depends on the complexity of the task [20, 40, 42]. Visualization with an interface can help [35, 40]. If interfaces in the form of displays are not available other **feedback methods** can ensure the ease of use by communicating information to the user and reducing uncertainty in using the robot [35, 40]. Autonomous robotic task learning, for example imitation learning, ensures the availability of a **large range of tasks** [39, 42]. The availability of general tasks adapted to the field of usage eases the distress in the lack of capabilities [9]. The **appearance and aesthetics** can influence the results of user's system perception. In the past, connections were found that due to insufficient aesthetics, users expected reduced social communication and isolation [9, 42].

Ongoing debates revolve around the *level of autonomy* and can vary from teleoperated systems to fully autonomous robots [5]. Recent studies have shown that more autonomy is not always better for the user [6, 35]. Autonomous behavior of the robot "allows reducing the human operator's workload when performing a task that can be repetitive and/or requires skills, effort or precision levels that exceed those of a human" [39]. If the robot produces more errors in task execution with a high level of autonomy, users tend to reject the system [6]. It can further lead to lost trust or a sense of lost control with unpredictable behavior of the system [35]. Validation functions communicating and verifying the next steps with the user can ease this issue [6]. On the other hand, the user's attitude towards a task influences the wish for a higher level of autonomy or a complete delegation of the task to the robot, e.g. if the user chooses not to perform the task [24]. In eye-tracking controls these levels of autonomy can be distinguished in teleoperated system, directionally controlled systems and systems with automated trajectory or grasp planning. This variation strongly influences the design process [17]. Directional gaze control is easy to learn, provides a sense of control, and reduces cognitive load [14, 15]. On the other hand, it is more time consuming to control each of the robot movements separately. Shared controls are mostly controlled by the user selecting the object via fixation, indicating the wish to interact with [12, 45, 49].

The *user's individuality and preferences* vary with personal metrics such as the user's age, level of disability, living arrangements, and familiarity with technology and affect the system's performance perception [42]. The **adaptation** of the system to user preferences is mentioned by various authors [6, 39]. The ability to adapt the system gave rise to Shared Autonomy approaches, "where the robot is capable of seamless adaptation of its autonomy level based on its own understanding of the human actions/intentions and of the surrounding environment" [39]. Incorporating the **preferences** of the user influences the perception and user satisfaction of the system [10, 11]. An example is the participant's preference for handing an object with a particular orientation [10]. A common factor, as known from the use of PCs, is the adaptation of the system to the user's preferences by offering a settings menu. Parameters such as the velocity of the robot should be adaptable [6]. Another factor is that offering a variation of input modalities (e.g. head or eye-tracking control instead of haptic control) makes it possible to tailor the system to the user's needs [6, 35]. Users want their interactions with the robot "to be customized to their impairment, their preferences, and their context" [35].

Other impact factors are a low maintenance system to ensure a **reduced workload for others**, such as family or caregivers [6]. Related to market introduction are factors such as the initial cost and the maintenance cost of the system [9, 42]. These may have less impact on the outcomes of the user survey, but are an important factor in the design of the system.

Due to the closeness between human and robot these technical and ethical challenges coexist [11]. In designing a well-balanced shared control, a trade-off must be found for all factors relating to technical and ethical challenges. In the following, we will present a solution that considers and balances the different influences.

2.2 Task preferences in assistive robot manipulation

Among the many daily tasks, research has identified the areas where people with physical disabilities prefer assistance. This can have significant impact on the design of the system, through the adaptation of grippers or, in the case of shared control, task automation.

The four most frequently mentioned tasks that an assistive robot should perform, were food related tasks (serving a meal, eating) [6, 7, 9, 11, 13, 34, 42], drinking related tasks [7, 9, 13, 42], picking up objects [7, 9, 13, 35, 42], and personal hygiene [9, 35, 42]. Picking up an object was further related to the location or a manipulation that was desired with the object such as picking it up from the floor or from a shelf, bringing it near, or moving it. Personal hygiene included various tasks such as shaving [7, 13], washing the face and hands, brushing teeth, combing hair, shaving, applying makeup [9], and dressing [11, 35].

The importance of being able to manipulate a wide variety of objects benefits the ability to get around, for example with an electric wheelchair by being able to move blocking objects out of the way. This is also a task desired by potential users [35].

Miscellaneous tasks were mentioned with taking medicine [35], working [35], leisure activities [34, 42], turning on and off switches [7, 13], opening and closing doors [7, 9, 13], scratching oneself [7, 13] and making tea. As sources from 2003 show, changing CDs and removing paper from fax machines are examples of how task preferences change over time [7, 13]. As the accessibility of smart home applications continues to evolve, it is expected that more tasks will become less important for robot assistance, such as flipping light switches or opening doors in the home.

Based on these results, a first selection of tasks was selected for the Wizard of Oz design to present in the studies. In Section 4.1 the literature findings were used to group the responses from the online survey and to compare results related to the change in task prioritization over time in Section 5.1.

2.3 Gaze as control input

The first eye-tracking controllers for robotic arms were developed as early as 2001 [30]. Since then, several systems have been developed, of which only a few have become commercially available [9, 17, 44]. They differ in the control approach used to guide the robot. A popular design approach is directional control, where the robot moves in the direction of gaze [1, 43]. Graphical User Interfaces (GUIs) are available in which the robot is moved with gaze-selected buttons, taking advantage of more accurate stationary eye-tracking systems [14, 41].

Going a step further, human intention in eye-tracking control can be predicted from task-related eye movements (anticipatory gaze [2]) based on the natural gaze behavior in hand-eye coordination [21]. Task anticipation has been explored to estimate task selection from the gaze pattern [26, 46]. It can be predicted before the action begins and during its execution [21, 39]. A crucial step in using gaze as control input is to decompose the behavior into subtasks to obtain specific gaze patterns that can be used to train AI models [22]. Another application is to use gaze as a complement to generate more dense and accurate information, as is done in Brain-Computer-Interface development [28, 36].

Especially reading task intention from gaze allows to use low-level cognitive inputs to realize systems with high autonomy, making it easier to interact with the system [21]. In contrast to these possibilities, there are some challenges that need to be considered when implementing gaze as a control input:

- **Unintended selection:** When gaze is used as a pointing device, e.g. to select an object, rules must be applied to ensure, that not all fixations are selection triggers. This issue is called the Midas Touch problem and describes an unintentional selection of an object [16, 29, 41]. Reasons include unintentional and reflexive eye movements, overlapping objects, distraction, stress, and limited accuracy of the eye-tracking device [25].
- **Context misinterpretation:** It is caused by overlapping objects or task ambiguity. When objects are close together and the eye-tracker accuracy is not sufficient, the gaze can be tracked on the wrong object leading to faulty interactions between robot and object [29]. In the interview conducted by Herr et al. [24] participants stated: "Well, now I look at you [the interviewer], but I actually focus on the bottle behind you. That would be difficult for the robot to recognize". This behavior suggests that attention to a particular location is sometimes unrelated to intention or cognitive process.
- **Physiological factors:** Physiologically, there are some factors that affect the accuracy of the gaze. Neurological conditions, fatigue, drooping eyelids and strabismus affect the functionality of eye-tracking devices [25]. The robotic workspace and gaze movements differ

in dimensions. Three-dimensional robot workspace has to be covered by two-dimensional eye movements. Eye tracking glasses have decreasing accuracy in the periphery of the field of view. When head movement is limited, as in the case of the stakeholder group, these peripheral regions are more likely to be used to fixate objects, leading to increased instances of contextual misinterpretation.

When such challenges occur, it can lead to frustration and high cognitive load for the user to avert such situations [16, 29].

2.4 Participation in assistive robot design

Aktion Mensch, a german organization for social projects, states that current assistive devices often fail to meet the needs of users [8]. In eye-tracking controls most studies recruit non-disabled people as participants [17]. Reasons why people with disabilities are rarely included in studies are recruitment challenges, small sample sizes, and transportation logistics [34]. As shown by Stalljann et al., control inputs are experienced differently by disabled and non-disabled participants [41]. Including people with disabilities helps in the design process of assistive devices by gaining insight into their lives and needs [4, 34, 42].

Nanavati et al. [34] discusses approaches based on three-dimensional key features to find the most appropriate study design for the goal of the study. The first dimension decides between individual or community-level participation. With individuals, the chance of a deeper insight into the user's life and preferences can be gained, while community work can lead to a broad insight from many participants. It also affects the time needed to conduct the studies and the connection between participant and experimenter. The second dimension highlights the logistical burden on participants and researchers. People with severe physical disabilities are usually dependent on their caregiver. Depending on the robot setup, it is easier to conduct studies at the participant's location, to reduce the need of special transportation and availability of caregivers. The third dimension describes the benefits to researchers and the community. Participants have an intrinsic motivation to participate in the design process of assistive devices and robots. They can benefit by providing impetus to adapt the systems to their needs. Researchers benefit by potentially making important connections for future work.

Although it does affect the length of the study, it is worthwhile to involve people with disabilities in the design process. These findings influenced the study design in Section 3.4.

3 Methods

In the introduction and background, we presented influencing factors and user challenges that affect the adoption rates of robotic arm systems. These challenges and factors were partially incorporated into the design of the system, presented in Section 3.1. Several groups of interest were interviewed with two study designs, to obtain broader feedback on the shared control design. The setup described in Section 3.3 and 3.2 was used in both studies. An online survey was sent to stakeholder groups, as well as their families and medical professionals and is presented in Section 3.4. Measurements were conducted to verify technical functionality and the reaction of participants interacting with the robot in person (see Section 3.5).

3.1 Shared control design choices

The initial idea of the system is to include a shared control in which parts of the robot movement are automated, such as trajectory planning, grasping and object manipulation. The level of autonomy is presented following the guidelines of Beer at a. (2014) [5].

What task is the robot to perform? This shared control is designed to assist people with severe physical disabilities in everyday tasks. Ongoing work is realizing a framework that can be extended to include everyday activities previously unknown to the robot. The first approach includes the tasks of grasping and handing drinks, filling a glass with a drink, and grasping and placing objects in locations selected by the user. These tasks can be performed in unsorted environments such as at home and in public places, e.g. a restaurant.

These tasks represent two of the most preferred tasks for robotic assistance in everyday life, as shown in Section 2.2.

What aspects of the task should the robot perform? The chosen input modality is eye-tracking, since eye movement is often unrestricted or only slightly restricted in contrast to other motor functions such as arm movement in cases of locked-in syndrome or cerebral palsy. The control is realized by fixating the desired object and the robot decides based on the selected object which available task to perform. Multiple objects can be selected by gaze to make task selection more robust. For example, looking at a cup could indicate that the user wants to drink from it, move it, fill it, or combine available tasks. By adding the ability to combine the cup with other objects, such as selecting a bottle or a location, the task can be distinguished into refilling the cup or placing it in the selected location.

Based on object and ask information, the robot performs the task autonomously. It determines the location of the object, a suitable grasp related to the task, and calculates the optimal trajectory.

To what extent can the robot perform those aspects of the task? The user is always in control of the robot. Emergency stop methods are considered to ensure the well-being of the user. Validation methods are planned to intervene in case of incorrect task execution before the robot starts the task. Settings are planned to reduce the robot's velocity if desired. With the implementation of dwell time selection of objects, incorrect interaction with the object is reduced with natural gaze behavior, thus minimizing the Midas Touch problem.

What level can the robot's autonomy be categorized? According to the classification of Beer et al. [5] robot autonomy is categorized as Shared Control with Human Initiative.

How might autonomy influence HRI variables? Reliability and functionality of the system must be given. Safety for the user must be ensured and is part of ongoing discussions. This system is designed to be easy to learn and use. Since there is no physical interface such as a display, the correct selection of the object depends on the accuracy of the eye tracker. Objects are selected by focusing on them in real-world settings. If the eye tracker is incorrectly calibrated, the gaze may not be tracked to the object due to high accuracy errors. This raises the question of how serious this error is in this setup, which will be tested with the Wizard of Oz setup. A wearable eye-tracker is used as input device. Influences on social variables such as aesthetics or the occupation of the voice by voice control, which could lead to a rejection of the system, are minimized.

3.2 Wizard of Oz design

Based on the results of the literature review, we decided to do an early evaluation of the design if it meets the expectations for the influencing factors given by the community. This approach has the advantage of shortening the development time by intervening in case of low acceptance or functional challenges. Therefore, the in the following used system represents a Wizard of Oz design, where the autonomously controlled robot tasks are performed by the experimenter, as seen in Figure 1. The objects were placed in a predefined position in the robot's workspace. All trajectories needed to realize the automated task execution were hard-coded and could be selected by the experimenter clicking on the program. The safety of the participant was ensured by separating the workspace of the participant and robot.

The experimenter was informed about the task sequence of the user and observed the participant's visualized eye movements in a live video on the monitor. As soon as the participant fixated on an object, the corresponding task was started via the robot's web interface.

Five tasks were selectable with the Wizard of Oz system: Picking up food with a fork, turning on a light switch, picking up and placing a block, scooping from a bowl, and filling a glass with water and handing it to the participant. Each task was related to different objects, as shown in Figure 2. The selection were based on the initial idea for the system and the outcomes of the literature review.

A video of task performance was created to be implemented in the online survey to visualize the function of the system (Section 3.4). This video is included in the Supplementary Materials. The system was also used in the hands-on study, where participants operated the system in a controlled environment (Section 3.5). Both studies were reviewed and approved by the ethics committee of the first author's institution.

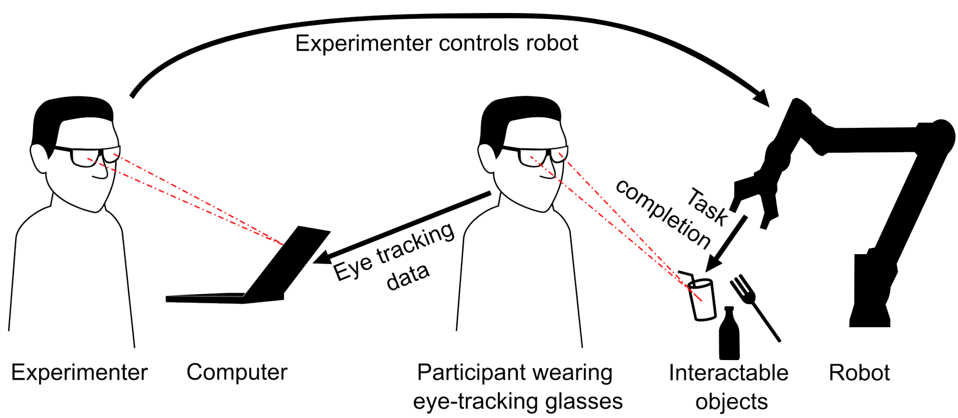

Fig. 1. Wizard of Oz design: The participant selects a task by focusing his or her gaze on the desired object. The gaze is visualized on the computer by displaying the live-video of the eye-tracker. The experimenter starts the task via the robot's web interface. The robot then performs the task and returns to the home position to wait for further commands. The home position is used as indication that the participant can select the next task.

3.3 Technical setup

The Wizard of Oz setup consists of a robot (Kinova, Gen3 with a gripper Robotiq, 2F-85) controlled via the standard web interface provided by the manufacturer. Data were recorded using wearable eye-tracking glasses (Tobii, Tobii Pro Glasses 3, accuracy = 0.6°). Gaze visualization, data analysis, and post-processing were performed using Tobii Pro Lab [37]. The control computer to move the robot and visualize the participant's gaze was placed 2 m behind the participant in the hands-on study so that the user was unaware of the experimenter's role.

3.4 Online survey

The online survey was chosen as the data collection tool because it provided a standardized way to present information and collect feedback. The purpose is to gain broad feedback from people with disabilities, their family members and caregivers to assess the usability and accessibility of the system. The logistical challenges described by Nanavati et al. [34] were minimized by providing an overview of the systems to the stakeholder group via online survey and video. It was advantageous

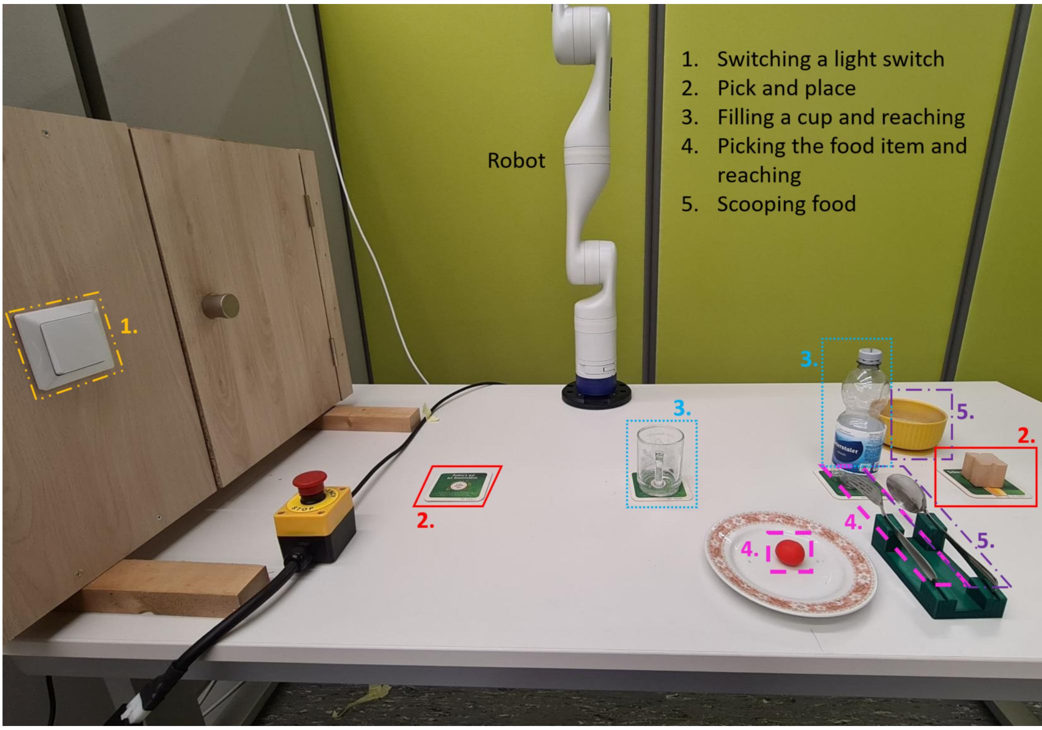

Fig. 2. Nine interactable objects were presented with which five tasks were performed. Participants were shielded from visual distractions by green walls surrounding the experimental area.

because it allowed immobile people to participate through the use of smart devices. People living at home could participate, as opposed to a real-world demonstration where the authors could only visit a few facilities. In addition, it offered the convenience of completing the survey at the participant's preferred time, accommodating those with complex schedules or who require assistance. Due to the anticipated limited availability of accessible computer controls, an extension was designed for family members and caregivers to obtain more comprehensive feedback. The purpose of this online survey was to answer the following questions:

- Are potential users able to use the system?
- Which tasks are preferred so that the robot has the greatest benefit in everyday life?
- Were the participants satisfied with the presented system?

3.4.1 Distribution method. The survey was available online from September 18, 2023 to January 22, 2024. 32 organizations in Germany, Switzerland, and Austria were contacted by email to reach the stakeholder groups. With reference to the distribution channels mentioned by Nanavati et al., we selected the following organizations and platforms [34]. Seven organizations shared the survey, such as FGQ (Paraplegic Support Association), LIS e.V. (Locked-In Syndrome Association), Diakonie (social services), Lebenshilfe (non-profit association), and the Swiss Paraplegic Centre. On social media, the survey was shared a total of three times by the authors' private accounts and by their institutions. FGQ shared it in their private Facebook group and a post was made in the private forum of the Swiss Paraplegic Centre.

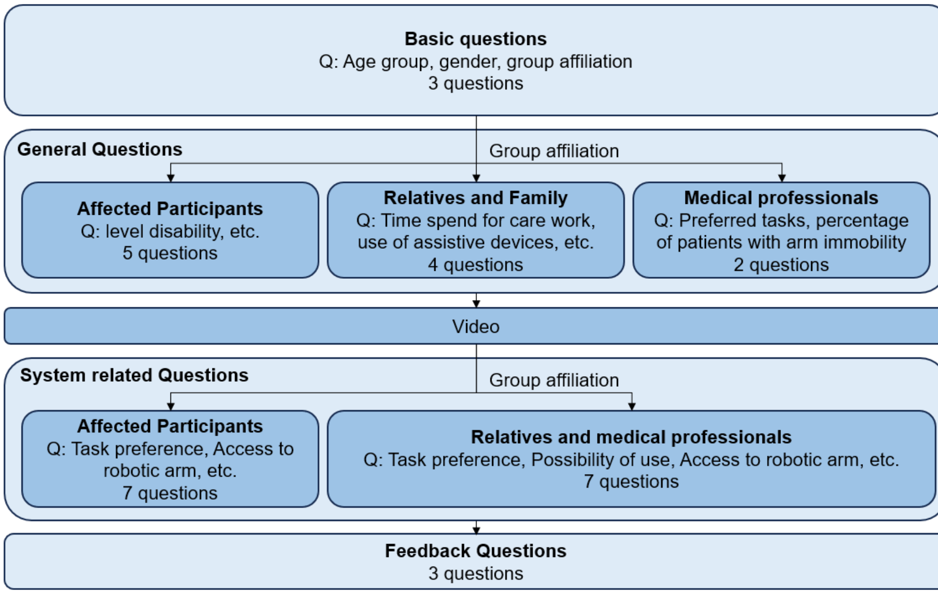

Fig. 3. Distribution of questions asked for each group. Q outlines the questions' context and the number of the questions for each category is given.

3.4.2 Survey structure. The online survey consisted of 31 questions divided into three groups and a video describing the eye-tracking control of the robotic arm structured as shown in Figure 3. The video showed the calibration process, the light switch task, the pick and place task, and the scoop task. In the survey, people with disabilities were asked questions to assess their level of disability and daily performance. Their need of the control modality, their access to assistive devices, and their evaluation of the presented eye-tracking control was surveyed. Open-ended questions were used to identify tasks that the robot should be able to perform. Family members and caregivers were asked about the amount of time they spend providing care and their estimation of the number of people with physical disabilities in their care facility. In contrast to the questions above, family members and caregivers were first asked what tasks they would like a robot to perform in general, regardless of the type of robot. In this situation, the participants were unaware of the robotic system. Then the system was presented and questions similar to the first questionnaire were asked. Finally, all groups were given the opportunity to provide feedback on the survey and the system itself.

All of the questions asked in the questionnaire, along with the participants' responses, are available in the Supplementary Materials. The survey was designed with LimeSurvey.

3.4.3 Evaluation method. A frequency analysis was performed to evaluate the users' perception of the system and the desired tasks. The tasks were categorized as introduced in Section 2.2: tasks related to eating, drinking, picking up objects, getting along, personal hygiene, and miscellaneous tasks.

3.5 Hands-on user study

In addition to the stakeholder evaluation of the system, the Wizard of Oz design was used to analyze real-world interaction. Evidence from the online survey suggests that participants are able to use the system based on their motor function and understanding of the system. The system realization might pose challenges in terms of functionality due to insufficient accuracy or natural gaze behavior. Participants were asked to interact with the robot to record gaze data that would be used to evaluate hardware constraints. Questions answered by this study include:

- Would the prototype eye-tracking controller work in the controlled environment of the lab?
- What are the technical difficulties with the design?
- Does participant perception vary greatly between the hands-on study and the online survey?

3.5.1 Procedure and participants. 24 participants took part in the study (7 female/17 male, mean age = 30.5, 11 non-prior experience group/13 prior-experience group with robots) to minimize the influence of learning effects or behavioral adaptation related to the 24 emerging permutations in the task sequence. Each participant was informed and gave consent to be included. They were asked to sit in a chair in front of the robot workspace. The setup and calibration of the eye-tracker was performed as described in [38]. Task start was selected by looking at one of two objects in the drinking, eating, and picking and placing tasks (see Figure 1). Participants chose the objects according to their preference. The experimenter performed the role of the automation as described in Section 3.2.

3.5.2 Data analysis. An evaluation of the Areas of Interest (AoI) and the dwell time is necessary to estimate the need for error minimization methods and to determine constraints for the object recognition algorithms. In combination with this technical evaluation of the system, the perception of the non-disabled participants was analyzed. In the Tobii Pro Lab events, Times of Interest (ToI), gaze movements during object selection, and Areas of Interest (AoI) were defined and labeled on the data. Metrics such as dwell times, which describe the total fixation time of an AoI relative to the ToI, and the number of missed hits were calculated by Tobii Pro Lab and exported for further analysis. Based on these parameters, the technical evaluation was performed.

Insights into the factors mentioned in Section 2.3 and Section 2.1 are gained by interpreting gaze data through Times of Interest (ToI), type of gaze movement, and Areas of Interest (AoI) to distinguish dwell times of AoI hits. These parameters can be used to describe the scene based on visual attention. In order to facilitate the understanding of such terms, definitions according to Holmqvist and Nyström [25] and Tobii [37] are presented below.

- Event: Describes in Tobii Pro Lab the time stamp when an event occurs. In this case it marks the start and end time of a task.
- Time of Interest (ToI): Interval between two related events
- Area of Interest (AoI): A polygon corresponding to the outline of an object. The resulting area describes a visual stimulus.
- AoI hit: Describes the entry of the tracked gaze into an AoI.
- Dwell Time: Describes the time the gaze remains within an AoI after the initial entry. In this study, the gaze was allowed to exit and enter the AoI. It was the sum of time while the gaze stayed within an AoI.
- Type of eye movement: In this study, fixations and saccades were of most interest. Fixations refer to the time the eyes remain stable and focused on a specific point or area of interest. It was not distinguished from smooth pursuit, in which the head is moved while the gaze rests on a fixed point in the scene. Saccades are rapid changes in gaze direction. They connect fixations. Other eye movements such as vergence movements and microsaccades were not investigated. For further information on gaze movement we refer to Holmqvist and Nyström [25].

4 Results

4.1 Online survey

20 out of 71 participants completed the survey. Of the 51 participants who filled out the survey, 36 surveys with no responses (N/A) had to be excluded. If participants completed part of the survey and answered more than page two of seven, the surveys were included in the study. Therefore, 34 complete and partially completed surveys were used in the analysis.

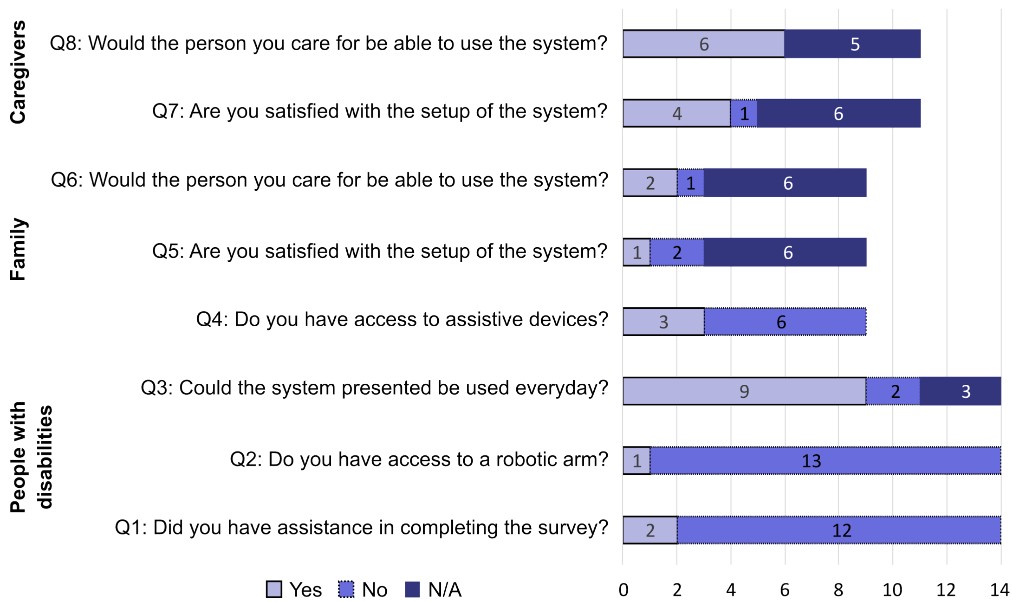

Fig. 4. Distribution of responses from online survey participants. Q1 to Q3 were answered by participants with disabilities, Q4 to Q6 by family and friends, and Q7 and Q8 from healthcare professionals.

Figure 4 summarizes the results of the survey. 14 participants identified themselves in the group of people with disabilities, eight in family members, and 11 in caregivers. Only once did the respondent not select one of these target groups ("other"). The authors decided to include the participant in the family group because of the affiliation description "Family but without care share". The results show that most people with disabilities were able to complete the survey on their own (Q1), leading to the conclusion that they have an assistive device that allows them to use a smart device. This conclusion is based on the participants' statement that most of them cannot move their hands (10 out of 14).

After viewing the video, participants were asked if they or the people they care for would be able to use the system. More than half of the participants confirmed this (17 out of 32; Q3, Q6, and Q8). Only three participants stated the opposite. The caregivers and family members were also asked if they were satisfied with the setup process (Q5 and Q7). Five stated they were satisfied, while three were not. One reason given was the amount of time it took to set up.

Participants were also asked what tasks they would like to accomplish with the system. The group of people with disabilities gave a total of 14 responses: Eating (3 mentions), drinking (2 mentions), reaching for cutlery, pushing buttons (elevator or electric door), applying makeup or brushing their hair, cleaning, scratching, opening a bottle, and lifting objects of various weights from the floor (2 mentions). Family members and caregivers were asked this question twice. First, they were asked to identify situations in which a robotic system could assist with everyday tasks while they were unaware of the system demonstration. Second, they were asked about the presented system. There were 13 responses to the first question. They rated the following tasks as useful: Making the bed, brushing teeth, assisting with eating, thromboses prevention, putting on socks, documentation, going to the bathroom, doing laundry, cleaning (2 mentions), assisting with walking, assisting with doctor's appointments and correspondence, silent alarm for service calls, and making phone calls. There were 14 responses to the second question: Eating (5 mentions), drinking, turning on lights, operating the aforementioned lift system, brushing teeth, preparing a drink, opening doors, lifting objects (2 mentions), making phone calls and moving objects. In comparison both questions show a high potential for robotic systems and digitization. In the first case, the focus is on assistance with household tasks and communication, while in the second, user-centered tasks are preferred.

4.2 Hands-on study

4.2.1 Gaze behavior analysis. The analyses of dwell times in relation to object selection events was used to find technical requirements on the eye-tracking controller. Assumptions such as correlations between object size and dwell time duration were investigated for the dwell time trigger anticipated in the design.

Table 1 shows the distribution of participants' choice of object selection and information about dwell time. A visual attention map is shown in Figure 5. The chosen interval was 1043 ms before the robot started to move and was based on the time steps made by the evaluation software. Both the data in Table 1 and in Figure 5 used the set intervals. In this time period, events such as searching for the object or deciding which object to select were excluded. It was ensured that the participant only focused on the selected object. The average duration of the test was 2 min 41 sec (SD = 9.8 sec).

The average dwell time was calculated to determine the maximum dwell time limit for the controller, including the time from fixation start until the robot moved. The longest possible dwell time for the participant's gaze in this setting was found to be 5.612 sec. In this interval, the gaze did not leave the AoI. It indicates that dwell time triggers can be set to high durations, but in the following limitations of the maximum dwell time are presented.

In this study, we assumed that the dwell time is longer the larger the object, due to the larger AoI. Accuracy errors would have less weight than in the small AoIs. The correlation between object sizes and corresponding dwell times were measured and are given in Figure 6. The bottle has a higher standard deviation in dwell time than the cup, implying longer dwell times in some participants' trials. As seen in Table 1 this is also visible in the dwell times above 500 ms. Reasons why the correlation may not apply are, for example, the fixation of the bottle cap, which is closer to the edge of the AoI than the cup handle. The gaze is more likely to leave the AoI, resulting in lower dwell times and indicating the influence of intention. In comparison, the fork and the block have approximately the same average dwell time and SD, despite having different object sizes. Our first hypothesis was extended that the geometry of the object also influences the dwell time. This influence is indicated by the small width of the fork handle, being less than 1 cm. When accuracy errors occur, it is more likely that gaze is tracked outside the AoI.

The influence of gaze direction was found by examining the low dwell times of the food item placed closest to the user. Looking at the gaze distribution in relation to the scene camera coordinate system, as shown in Figure 7, it is evident that participants tended to move their head to center their gaze when looking at a peripheral object to the right or left. In contrast, participants tended not to move their head when looking down. The detected gaze location was less accurate, due to higher scatter closer to the eye-tracker's periphery. Physiological impact cannot be excluded such as shadowed pupils by the eyelashes. This resulted in seven missed AoI hits for the food item.

Table 1. Information about distribution of selection by participants, dwell times and missed AoI hits.

Object	Number of selections	Occurrences of dwell time over 500 ms	Missed AoI hits
Bottle	11	82%	0
Platform	7	87%	1
Cup	13	92%	0
Light switch	24	75%	4
Fork	9	58%	5
Block	14	56%	5
Food item	11	38%	7

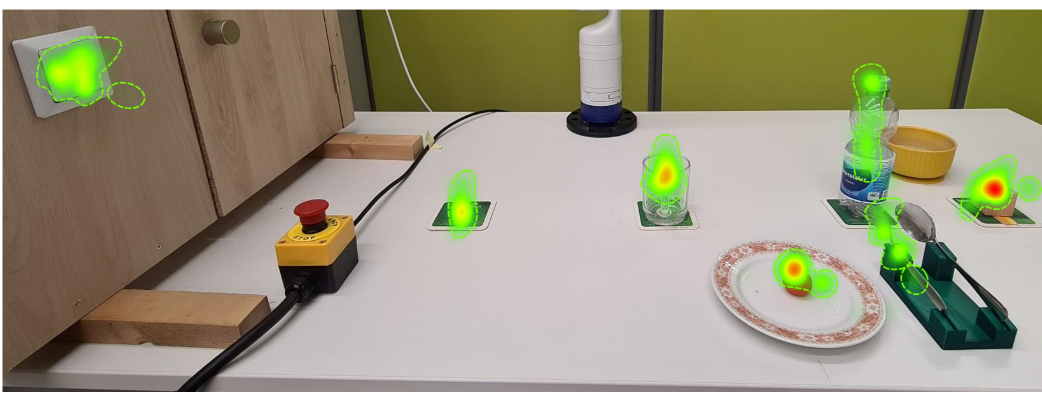

Fig. 5. Heat map visualizing the attention of participants during task selection (absolute duration), mapped to the snapshot of the experimental setup. Red areas indicate frequent fixations, green less fixations. Areas without coloring indicate no fixations within the observed intervals. Dashed outlines were added manually to better distinguish the edges of the hotspots.

Significant correlation was investigated between dwell time, object size, and gaze direction towards the object. The Shapiro-Wilk test (H = 0.771, df = 97, p = <0.001) and the Levene test (H = 2.658, df1 = 6, df2 = 90, p = 0.02) showed no normal distribution or homogeneity. A Kruskal-Wallis test was applied and showed significant differences ($H(6) = 17.442$, $p < 0.008$). Post-hoc analysis using Dunn's test with Bonferroni correction revealed significant differences ($p < 0.05$) between the following pairs: food item and bottle, food item and platform, food item and light switch, food item and cup, and block and light switch. These results indicate that the measured data for the food item are significantly different from the other objects. Spearman's ρ was used to analyze the correlation between object size, object position, and dwell time. The frame in Figure 7 was evenly divided into five-by-five sectors in horizontal and vertical directions, so that gaze location could be described by a coordinate map. The analysis showed that dwell time and object size ($\rho = 0.373$, $p < 0.001$) as well as dwell time and offset in y-direction ($\rho = 0.263$, $p = 0.009$) were positively correlated. The correlation between the offset values in y-direction and x-direction is weaker and does not correlate with dwell time ($\rho = 0.160$, $p = 0.116$). This indicates that the assumption that the dwell time is influenced by gaze location towards the object and the object size is correct.

4.2.2 Perception of hands-on application. In general, satisfaction with the system was expressed in the hands-on study. Participants responded with following comments: 9 positive, 3 negative, 9 times

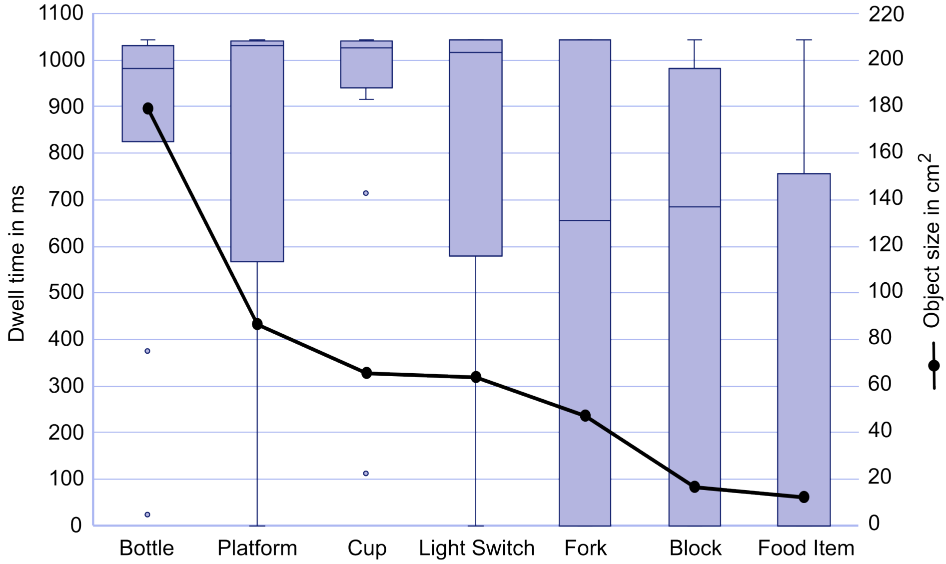

Fig. 6. Correlation between object size, missed hits and dwell time for the selectable objects. Dwell time is given as the total duration of gaze within the objects AoI 1043 ms before the robot started moving. The line in the box plots marks the median, confidence intervals are given at 95%.

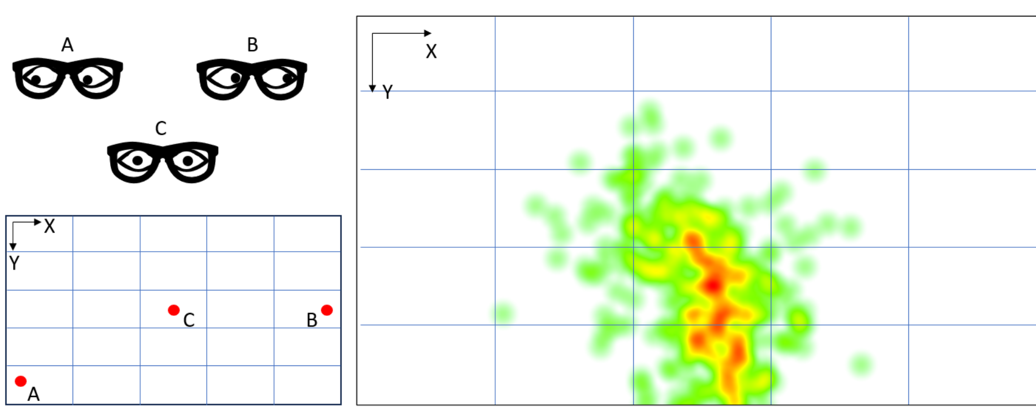

Fig. 7. Left: Exemplary representation of the viewing directions to explain the resulting heat map. Visualization of the viewing point in relation to the visual field of the scene camera. Right: Heat map of gaze position during task selection. The field of view is divided into 5 by 5 fields indicating a 5-section coordinate map used to determine the correlation between dwell time, gaze location, and missed AoI hits. Gaze direction was mostly centered and downwards while task selection.

positive and negative, and 3 times with no comments. All statements can be found in Appendix A. Differences were found between the responses of people who work regularly with robotic arms (called prior-experience group below) and people who have no experience with robotic arms (called non-prior-experience group). The non-prior-experience group gave mostly positive comments and focused more on the description of tasks, while the prior-experience group focused on robot kinematics, robot behavior, and user safety, which partially included negative aspects.

While the non-expert group reported being interested, entertained, satisfied, and impressed, they also perceived confusion and uncertainty. The task design itself caused confusion, as participants were not sure how to react to the glass presented by the robot. Considering a real-life application of filling the glass, one of the participants expressed fear of overfilling the glass. Regarding the robotic system, they were satisfied with good reaction time and intuitive control. The velocity was ambivalent, with some participants saying it was just right and others saying it was too slow. Importantly, users reported feeling safer because the robot's movements were limited to the edge of the table. The fork movement may have had an unsettling effect on the person, as they reported that the fork was not close enough to eat or at the right height for their mouth.

The prior-experience group comments were mostly negative about the robot's trajectory and the measurement setup. For example, the gripper could crush someone's hand if the user reached into the setup, due to the lack of pressure sensors. The placement of the emergency stop was a concern for the well-being of future users due to its distance from the participant. The shaky movements of the robot, the non-optimized trajectories, and in one case the robot accidentally touching the bottle while moving to the next object were mentioned. The perceived motor vibration was uncomfortable and the sound of the dropped fork was too loud. Reaction time and object recognition were mentioned as positive. In addition, two participants from both groups stated that they felt uncertain that the robot would stop the task if they looked away or at other objects while the robot was performing the task.

5 Discussion

In Section 5.1 two of three usability questions and in Section 5.2 two of the three functionality questions are answered asked in the Methods. In Section 5.3 the last question of both studies will be discussed, which combines the perception of the online study and hands-on study. The resulting adaption features to improve the initial design are given in Section 5.4.

5.1 Usability

5.1.1 Are potential users able to use the system? Yes, the survey showed in Q3, Q6, and Q8 (Figure 4) that most participants are able to use the system based on the video presentation (Answers: 17 yes, 3 no, 14 N/A). The high amount of N/A results were a result of including partially filled out surveys.

In the open-ended questions, statements were made that the participants would like to have more information about the system to better evaluate the maintenance needed and the function of the system. These requests did not imply that the participant would change his or her mind after receiving the additional information. One participant stated "I wonder if the system can be used by people with intellectual disabilities due to their reduced cognition". This underlines the importance of considering a variety of disabilities in the design process of such systems in order to make them accessible to a wide range of users. It highlights again the necessity to involve the community in the design process.

5.1.2 Which tasks are preferred so that the robot has the greatest benefit in everyday life? The categories of eating, drinking, environmental interactions, pick and place, personal hygiene, and miscellaneous tasks were found in the literature and are listed in Section 2.2. The participants' responses from Section 4.1 were sorted into these categories that lead the distribution in Figure 8. The most requested task in the online survey that the robot should perform is assisting to eat or drink, followed by environmental interaction, which includes turning lights on and off, pressing buttons, opening doors, and pick and place objects. Picking up and moving objects was mentioned in different contexts such as moving heavy objects out of the way. Personal hygiene consisted of a variety of different tasks including doing makeup and hair, brushing teeth, and cleaning. Miscellaneous tasks included making phone calls and scratching themselves. These results can be corroborated with other findings [13, 42, 48]. The variety of tasks expressed shows that participants were not biased by the tasks shown in the video.

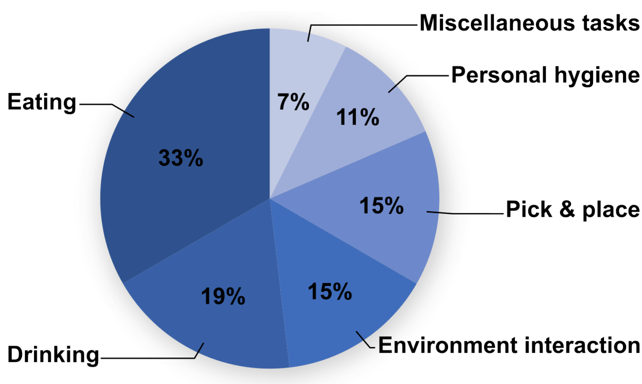

Fig. 8. Classification of all mentioned tasks in relation to the presented system. 28 tasks were classified into six categories containing the tasks mentioned by the participants.

Brushing one's hair, applying makeup, or scratching are everyday tasks that require close human-robot interaction while ensuring the safety of the user. The shared control approach presented would require face and body recognition if the user is unable to move their head to a certain position. Ethical questions arise when personal data is recorded, including physical and physiological appearance. Current discussions in this area suggest that the user must be informed about the system functions and the personal data collected. This would allow the user to decide whether the privacy limitations or the benefits of the system outweigh [18]. The aim must be to present this information in simple language so that people with physical and cognitive disabilities can understand it and make decisions.

5.2 Functionality

5.2.1 Would the prototype eye-tracking controller work in the controlled environment of the lab? Initial testing showed that 70% of object selections would result in selection success when the dwell time trigger is set to 500 ms. Although, dwell times can be shortened to enhance selection success as shown in other literature [25], this could lead to an unintentional object selection as described in Section 2.3. An appropriate threshold must be explored with the prototype system.

Accuracy issues are one of the main reasons why gaze was tracked outside of an AoI. Therefore, influences on AoI misses and dwell time were investigated in Section 4.2. Four dependencies were found:

- Object size: As shown in Figure 6, object size correlates significantly with dwell time. Small objects like keys are part of everyday activities. Excluding such objects from interaction, would lead to major drawbacks in participation in daily life. The available workspace is limited by the length of the robotic arm. This also limits the relative size of the object in the camera scene. With this limit, the resulting accuracy error can be calculated and checked with the desired interactable object size to estimate if this would cause problems. In this case, the accuracy of the eye-tracker is $\Delta_{deg} = 0.6°$. With an effective workspace of $d = 89.18$ cm for the used robot arm [27], the maximum accuracy error is 9.34 mm ($\Delta = d * tan(\Delta_{deg})$). Since all selected objects were larger than 9.34 mm, it is assumed that the prototype would work.

- Geometry: The AoI of the fork could lead in a failed selection due to its width. Currently, there are two approaches in planning for estimating object outlines. Object recognition can be used to create bounding boxes, solving the issue due to the new geometry. Overlapping of bounding boxes may occur more often, leading to unintentional object selection and context misinterpretation. Object segmentation can lead to boundaries which fit to the object's outlines. In this case the geometry of the object would be traced with high accuracy, solving the bounding box issue, leading back to the initial width issue.
- Gaze location towards the object: In the eating task example, participants tend to move their head to the left and right instead of up and down (see Figure 7). The resulting higher accuracy error was due to the glasses periphery. Considering physical disabilities of potential users, an immobility of the head cannot be excluded.
- User intention: Participants were instructed to focus their gaze on the selected object, but not on which region in detail. In the case of the bottle, the task was to fill the glass. The bottle needs to be opened first, which explains why the bottle cap was fixated, indicating the hand-eye coordination and intention behind the task as discussed in Section 2.1.

5.2.2 What are the technical difficulties with the design? Ambiguous object selection can occur due to object overlap and was found in the case of the fork (see Figure 5). In addition to the accuracy challenges, robust object selection may be the most difficult challenge in implementing the prototype.

Task validation methods and emergency stops must be ensured, as found in Section 2.1. Approaches such as looking into the corner of the field of view could be challenging to interpret as an emergency stop because it is processed as the same data type as prolonged blinking in the eye-tracking software. Another approach describes the inclusion of gaze gestures (unique sequence of eye movements [1]). It needs to be verified whether such a cue would be able to perform for a person in an emergency situation. For task validation, the system needs to be enhanced with feedback methods to communicate the expected task by the robot.

5.3 Differences between Online Study and Hands-On User Study

5.3.1 Were the participants satisfied with the presented system? In both studies, participants were mostly satisfied with the system. The challenges that were uncovered are summarized in Section 5.4.

5.3.2 Does participant perception vary greatly between the hands-on study and the online survey? The unstructured in-person interview with participants in the hands-on study and the open-ended questions in the online survey, provided more diverse feedback on this shared control design. The results are consistent with and extend current literature in this area. It adds information for the design of gaze-controlled assistive robotic arms. Perceptions of the system do not vary but, highlight different aspects of the design.

Involving the stakeholder group yielded insights about everyday tasks and their daily life with their disability. The prior-experience group revealed potential drawbacks in the technical design process, such as concerns about safety, kinematic selection, and trajectory planning. Although the non-prior-experience group did not have in-depth feedback on certain aspects of the life with a disability or technology, they helped build a larger pool of participants to measure gaze behavior. In addition, their perception of the robot was more curious and at the same time hesitant than that of the prior-experience group, due to the novelty of robot interaction. Since robotic arms are rarely available to people with disabilities, it is reasonable to assume that in a real-world test, people with disabilities would respond in a initial robot interaction similarly to the non-prior-experience group.

5.4 Adaptation of the initial Shared Control design

Based on these results, the design can be refined to meet the participants' expectations of the system. The next step is to automate the experimenter's control task so that the robot can autonomously perform tasks selected by the user. The framework must have the following features to realize the system:

- Gaze detection on objects: Due to the outcomes in Section 5.2, several approaches are followed to detect objects in the scene camera of the eye-tracking glasses. Unintentional selection and context misinterpretation will be estimated with the prototype.
- Task availability: The survey showed that the desired tasks were in line with the participants' expectations. Eating was the most frequently mentioned task. However, handling a fork is a safety risk, when the robot manipulates the fork autonomously and has to be handled appropriately.
- Task selection: The expected prototype will implement objects associated with multiple tasks. Testing has shown that if the dwell time is set correctly and the algorithm is designed to wait for multiple objects to be selected, the task should be robustly selectable. Dwell times of 500 ms and less were found to be appropriate. As mentioned in Section 2.1, feedback strategies need to be evaluated and integrated into the control to ensure the user.
- Trajectory, grasping and collision avoidance: The robot has to perform the task by itself. In the current version, the robot's trajectory was programmed and the objects were placed at the same location for each test. In a real-world scenario this would not meet the user's expectations. Solutions were found as presented in Section 2.3) and depend on the approach chosen for object gaze detection.
- Adaptation: On behalf of the ambiguous results of the robot's velocity perception, an adaptation setting will be included in the prototype so that users can adapt the system to their liking such as robot velocity.

6 Limitations

Additional questions: The safety concerns were not reflected in the responses to the online survey. Including questions such as "Would you feel safe interacting with the robot?" would provide a more comprehensive understanding of this topic. However, other studies show that potential users are more likely to accept the risks of using the system than to reject it and become dependent on caregivers or family members [4]. This can also be seen here, as the robot-experienced group is aware of the risks of human-robot interaction but is not fearful of interacting with the robot. **Specific Wizard of Oz design:** The Wizard of Oz system is an eye-tracking-driven design in which objects are selected without the need for a GUI. This approach is uncommon since prototype systems face challenges such as interpreting the desired task, error estimation due to head movements, and a lack of feedback modalities [17]. Researchers using these adaptation suggestions should check whether the findings can be applied to different input designs. **Generalized approach:** This approach was not tailored to specific disabilities, so it may lack details necessary to adapt to individual users' needs. Future work can use this generalization to more easily locate these demands.

7 Conclusion

The goal of this work was to obtain feedback on an eye-tracking-driven shared control for Assistive Robotic Arms to identify community expectations, desired tasks, and technical challenges. The factors for a successful implementation of a shared control were identified and presented. A Wizard of Oz design was created prior to prototyping, as suggested by other researchers.

Based on this design, two studies were conducted. An online survey designed for people with disabilities, their families and friends, and caregivers provided feedback on the community's expectations for the system, as well as the desired task the robot should be able to perform. A hands-on study with participants with and without robotics experience provided insight into the technical requirements and feedback differences between the video presentation available for the online survey and the real-world application. Gaze data was recorded to measure dwell times and influence dependencies related to the eye-tracking control.

Dependencies for the design of eye-tracking-driven robot controls were uncovered, ranging from user demands on task prioritization, to accuracy limiting factors in eye-tracking. As a consequence, improvements to the initial idea were presented to facilitate the usage of the system.

Acknowledgments

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A Participant statements of hands-on study

In the following the statements of participants of the hands-on study are listed. All statements were translated by the authors to english. Participants without any statement to the system were not listed below.

Table 2. Statements of participants. Prior-experience group: Exp., Non-Prior-experience group: Non-Exp.

P	Exp./ Non-Exp.	Statement
1	Non-Exp.	By noting that the robot does not go over the table, P1 was reassured. “apprehension, causious” system if not had stated, Glass’s task: fear of overspilling and dropping the cup in the real task.
3	Non-Exp.	Food task: Lifting a fork so high that you only had to grab was cool. Light switch was hit centered, that was cool. The handle of the cup was held towards the person. That was very practical if you wanted to grab it.
4	Non-Exp.	Fork task: Test person was confused because the fork pointed to a fixed point and did not go in the direction of the mouth. General: Confused as to whether the robot cancels the task when looking at another object.
5	Non-Exp.	Movements too slow for everyday use. However, it was satisfactory for an initial test.
6	Non-Exp.	Food task: Serving food was interesting. Glass task: The glass slipped a little when I put it down. There was no straw in the glass, so it wasn’t clear why the robot handed the glass flat.
7	Non-Exp.	Open gripper is uncomfortable when it points at you. Velocity was good.
10	Non-Exp.	General: By saying that the robot does not reach over the table, the action was not scary.
11	Non-Exp.	General: Responds quickly, which is good. Intuitive operation. Once you know where the robot stops it is less intimidating/scary.
13	Exp.	Fork task: First close the gripper a little before gripping the fork completely, less risk of crushing the hand. General: Emergency stop is poorly positioned.
14	Exp.	Kinematics moves spongily, drinking task: Kinematics has touched the bottle.
15	Exp.	When the fork is dropped, a loud unpleasant noise is heard from the drop.
16	Exp.	P16 asked whether tasks are aborted if you accidentally look at other objects. Waiting time is appropriate until the robot moves. It does what you want (intuitive control). Kinematics vibrate during movement, which is negative.
17	Exp.	Robot is shaky, jerks. Selection process: Fear of triggering the wrong action when looking at the wrong object.
18	Exp.	Movement was a little too fast to the light switch
22	Exp.	With pick and place, it was assumed that either the block or the platform could be gripped. Accordingly, P22 was confused.
23	Exp.	Robot trembles, trajectory not optimal, bottle badly twisted while handled.
24	Exp.	Fork was recognized well, even though you looked briefly at the bottle during the time you had to aim. The pause between aiming and starting the pick and place task was too long!

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