# A BCI-controlled Robot Assistant for Navigation and Object Manipulation in a VR Smart Home Environment

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Abstract: BCI-controlled smart homes enable people with severe motor disabilities to perform household activities, which would otherwise be inaccessible to them. In this paper, we present a proof of concept of an assistive robot with telepresence functionality inside a Virtual Reality (VR) smart home. Using live EEG data and a P300 Brain-Computer Interface (BCI), the user is able to control a virtual agent and interact with the smart home environment. We further discuss the potential use cases of our proposed system for patients with motor impairment and recommend directions for future research.

## 1 INTRODUCTION

Brain-computer interfaces (BCI) are communication systems that get their input from brain activity and translate them into output commands for external devices without requiring the user to move physically (Wolpaw et al., 2002). Therefore, BCIs can help patients with motor impairment to regain the ability to communicate and interact with their environment through various control paradigms. There are different methods to collect a user's brain activity, among which electroencephalography (EEG) is the most popular as it is non-invasive and offers a high temporal resolution (Abiri et al., 2019).

Depending on the EEG component extracted from the brain, a BCI system can be classified into three major paradigms; P300, steady-state visual evoked potential (SSVEP), and motor imagery (Abiri et al., 2019). The P300 paradigm relies on positive deflections in form of an event-related potential (ERP) that are elicited approximately 300 ms after encountering an intended stimulus in an oddball paradigm (Mattout et al., 2015). Therefore, by comparing the event-related potentials induced in a sequence of stimuli presentation, P300 BCIs can identify a user's choice of target. The P300 paradigm requires less user training than other paradigms (Guger et al., 2009), making it a promising tool for the design of BCI-controlled interactive environments (Fazel-Rezai et al., 2012).

BCI-controlled smart homes have been studied using both virtual reality (VR) simulations and physical prototypes, which are often limited to a single appliance or function (Edlinger and Guger, 2011; Edlinger et al., 2009; Sahal et al., 2021). A limitation of previous BCI smart home studies is that they have only focused on simple tasks that can be accomplished by sending digital commands to smart devices. For instance, Edlinger and Guger (2011) presented an experiment involving smart home control inside a virtual environment using a modified P300 speller that allowed the user to control lights, turn the TV on or off, select TV channels and adjust the volume. A more recent study by Sahal et al. (2021) used augmented reality (AR) combined with a limited prototype to accomplish similar tasks by utilizing the inbuilt capabilities of a smart assistant (Google Assistant).

Although these setups can give patients control over their entertainment systems and ambiance, they do not address the most basic needs of immobile patients; e.g. retrieving a glass of water, medication, or food. The missing component is the ability to move and manipulate objects. Combining a BCI-controlled environment with a robot that could facilitate physical tasks, such as object retrieval, could address these needs.

### 1.1 Robot-assisted Smart Environments

A number of past studies have attempted combining robot assistants with smart home applications (Do et al., 2018; Wilson et al., 2019). These studies are primarily focused on elderly healthcare to improve in-

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dependent living. For instance, Koceski and Koceska (2016) developed a telepresence robot that was able to drive around and use an extendable arm to grab and fetch small objects. Additionally, the head of the robot was equipped with a tablet that included an integrated camera. This had two benefits: a live stream of the robot's location was provided to the users so that it could be operated even when out of sight, and the user was able to create a two-way video call, which allowed them to connect with caregivers, relatives, and friends. Participants reported their perceived 'functionality usefulness' of the robot on a five-point Likert scale. Importantly, both navigation and the manipulator functions achieved scores of 3.0 and higher, indicating high user acceptance.

Other studies have shown that telepresence robots can help patients who are limited in their interactions with the outside world feel more socially connected, which could alleviate or prevent psychological problems stemming from loneliness and isolation (Hung et al., 2021; Moyle et al., 2017; Niemelä et al., 2021; Odekerken-Schröder et al., 2020; Wiese et al., 2017). For instance, Niemelä et al. (2021) conducted field trials with a duration of 6-12 weeks to study the effect of telepresence robots in elderly care facilities. The authors found that telepresence robots made the patients feel as if their family members were present, which had a positive effect on their social well-being. Another study addressing loneliness and isolation during the COVID-19 pandemic by Odekerken-Schröder et al. (2020) found that in addition to facilitating social ties between humans, the robot itself can be perceived as a social companion that plays the role of a personal assistant, a relational peer, or an intimate buddy. A similar effect was observed using a companion robot for dementia patients in Hung et al. (2021), where the robot was perceived as a buddy that facilitated social connection and mitigated feelings of loneliness.

While the above-mentioned studies highlight the potential of robot-assisted environments for many user groups, they are often focused on able-bodied patients who can interact with the robot through speech or a handheld device such as a phone or tablet. As these input devices require motor control, patients with motor impairment would not be able to use the systems. For some patients with motor impairment, gaze control or voice control are alternative options. Tele-operated robots that are controlled by eye-tracking have been used in studies with a view of assisting disabled patients (Watson et al., 2016; Zhang and Hansen, 2020), and similarly, voice control has been used as an additional control option for a smart home prototype (Luria et al., 2017). However, there are severe cases of motor impairment where neither speech nor gaze control is possible. Patients who suffer from locked-in syndrome, e.g., amyotrophic lateral sclerosis (ALS) patients, are unable to use any traditional input methods. For these patients who can not communicate through any physical medium, BCI systems are the only means that would enable them to express their needs or gain control over assistive devices that could reduce their reliance on caretakers (Wolpaw et al., 2002).

For instance, in the study of Spataro et al. (2017) focusing on ALS patients with locked-in syndrome, a P300-based BCI was used to control the humanoid NAO robot. The authors found that a majority of the patients were able to control the robot successfully to fetch a glass of water. This suggests that a robot-assisted smart home environment could be a possible solution for increasing independence and quality of life for ALS patients. However, the NAO robot used in this study is a small size robot not capable of navigation. Therefore the water-fetching capabilities were tested either on a fixed office desk or a wooden board laid over a bed, neither of which would be a realistic scenario for a bed-bound patient (Spataro et al., 2017).

In this study, we demonstrate a proof of concept for a P300 BCI-controlled assistive robot in a virtual smart home. Specifically, we will focus on complex tasks that are needed for independent living but cannot be accomplished without object manipulation. A VR environment is used to simulate an IoT-based smart home, which can be controlled directly for simple tasks such as controlling lights. A virtual robot in the same environment facilitates complex tasks, such as object retrieval, once such intention is decoded from the user's brain activity. VR provides a feasible platform for rapid prototyping and user evaluation as opposed to physical smart home environments that are costly and laborious to create (Holzner et al., 2009). By combining a BCI system with a robot-assisted smart home, our proposed system illustrates a proof of concept for future smart homes that can significantly increase the independence and life quality of patients who are immobile or experience reduced mobility.

# 2 SYSTEM DESIGN

## 2.1 Virtual Reality Simulation

The VR smart home environment was developed in Unity, which is a widely used cross-platform game engine. We used an add-on called SteamVR,

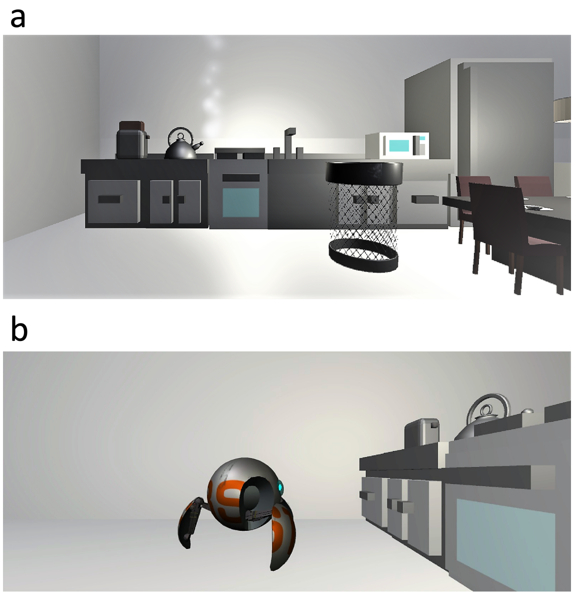

Figure 1: (a) VR simulation of the smart home environment and (b) Virtual robot assistant

which is compatible with nearly all head-mounted displays (HMD). The HMD employed in this study was an Oculus Quest 2. The environment consists of one room with kitchen appliances, lights, and basic kitchen furniture (Figure 1). The 3D assets used in our environment are, except for the kettle and toaster, from the Unity Asset Store (Demon, 2020; Q! Dev, 2018; Rubens, 2017; Studio, 2021). We developed the remaining assets using Blender. The environment can be viewed either from the third-person perspective of the room or as a moving first-person perspective that follows the robot, depending on the user's preference.

The appliances in the VR room were designed to provide the user with affordances for the actions they can take. During interaction, a custom-designed controller board is displayed at the corner of the view-field in the HMD, which gives possibilities for five navigation and four object manipulation commands

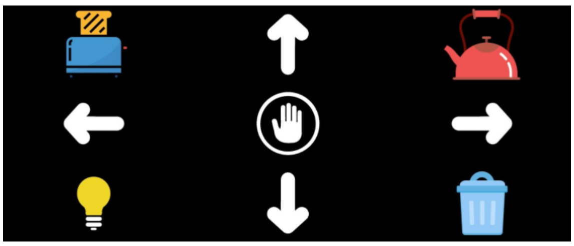

Figure 2: Custom-designed P300 controller board for a robot-assisted smart home environment.The arrows and stop icon are for direct user-controlled robot navigation. The remaining four icons give high-level commands for the robot and smart home environment (e.g. make toast, switch on/off the lights, make tea and clean up trash).

(see Figure 2). The navigation commands allow the user to directly control the movement of the robot in four directions and subsequently halt the movement. The icons with household items (toaster, kettle, light bulb, and trash can) give high-level commands that initiate action sequences for four tasks: making toast, turning the kettle on, turning the light on, and cleaning up. The commands include both simple tasks that can be achieved without robot assistance by communicating directly with the smart home appliances (e.g. switching on the lights), and complex tasks that require interaction between the robot and the smart home (e.g. making toast, which requires the robot to insert bread into the toaster and deliver the toast to the user). Additionally, the cleaning up task involves shared control from the user to avoid potential issues around misidentification of disposable items: when the cleaning mode is initiated, the robot can be moved around by the user to locate items that need to be taken to the trash can by the robot (outside of cleaning mode the robot would not dispose of items).

The VR environment is responsive to the user's choices, giving visual and auditory feedback once their selected action is successfully recognized and carried out. Specifically, a toaster selection is followed by a toast coming out of the toaster, the kettle displays a smoke animation, the light bulb icon switches on the virtual lamps increasing the luminance of the room, and the trash can icon triggers a cleaning animation carried out by the robot assistant.

## 2.2 P300 BCI

Brain activity is recorded using the Unicorn Hybrid Black system (g.tec neurotechnology GmbH, Austria), which is a wireless EEG cap (Fig. 3a). The signals are collected from 8 channels according to the 10-20 international system (Fz, C3, Cz, C4, Pz, PO7, Oz, and PO8). The channel positions are visualized in Fig. 3b. The ground and reference electrodes are placed on the mastoids of the subject using disposable adhesive surface electrodes. To inspect the EEG signals and extract P300 potentials, we used the Unicorn Suite software. This software includes Unicorn Recorder and Unicorn Speller; the former is used to check the quality of the signals and the latter is used for the P300 paradigm.

The Unicorn Speller runs on MATLAB Simulink and includes three main modules; signal acquisition and processing, feature extraction, and classification (Fig. 4) (Guger et al., 2009). The Speller graphical user interface (based on which the controller board was designed, Fig. 2) contains rows and columns of stimuli that flash at a certain frequency. The user is

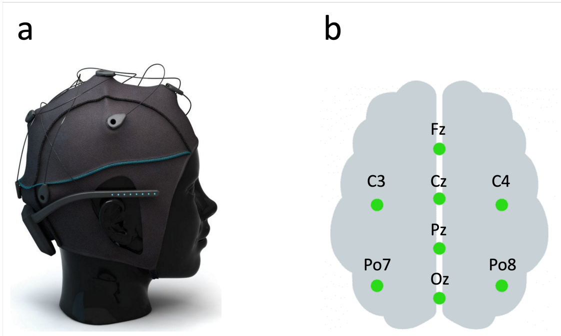


Figure 3: (A) Unicorn Hybrid Black system, (B) electrode positions for the P300 BCI interface.

asked to focus on one item and count the number of times it flashes while ignoring other items. Every time the target item flashes, a P300 response is generated and reflected in EEG signals. By comparing the timing of the P300 response in the recorded signals and the flashing sequences provided by the interface, the system can identify the target item that was chosen by the user.

## 2.3 System Architecture

The general architecture of the solution consists of two components; the VR smart home and the P300 BCI system. The two are connected using the P300 controller board (Fig. 2) which provides visual cues to the user. The controller board presents a 3 by 3 table of options, enabling both navigation and object manipulation commands for the assistive robot.

Using the hardware mentioned above, we created a BCI-VR loop (Fig. 4) whereby the user's brain activity is recorded by the EEG cap as they observe the VR environment in a HMD. The P300 controller board is presented as a second display at the bottom corner of the visual field in the HMD. The P300 BCI system controls the flashing sequence of the icons on the controller board. The flashes last 150 ms, with no delay between them. The user is instructed to choose their command of choice by focusing on the representing icon on this board and silently count the number of flashes. The BCI system would then match the timing of the flashing with the P300 responses in the brain to predict the user's chosen command. The command recognized by the BCI system is then translated into a control signal for the VR environment (e.g. switch on the lamp), following which the user receives visual feedback for their chosen action in the HMD.

# 3 DISCUSSION

The current study proposed a proof of concept for a BCI-controlled smart home in VR that was mediated by a telepresence robot. The system architecture proposed in this study followed the shared control paradigm as suggested by Koceski and Koceska (2016), which allows the user to give the robot commands on a high level, such as moving in a particular direction or grabbing an object, while the lower-level tasks needed to accomplish the goal are performed automatically by the robot. Assigning tasks to the robot on a high level is assumed to be more feasible for a user with motor impairment compared to having control over low-level movements needed to complete the task. This should keep the training time required to use the system relatively low while still giving the user a sense of control.

The integration of a telepresence robot with a BCI-controlled smart home offers several advantages to immobile patients. It emulates the ability to move around in an environment when walking or wheelchair operation is no longer feasible. Additionally, it can increase perceived social presence through communicating with caregivers or loved ones who are physically out of reach (Koceski and Koceska, 2016; Moyle et al., 2019; Niemelä et al., 2021). Furthermore, the sense of agency and embodiment associated with BCI-controlled telepresence robots have been previously shown to increase user performance on the BCI task and hence the quality of interaction with the system (Alimardani et al., 2013). For this effect, a first-person view of the environment streamed by the robot is essential. In our current VR design, either first-person view or third-person view can be manually chosen at the beginning of the interaction. In future prototypes, a BCI toggle could be added to enable the user to change the view dynamically.

Usually, telepresence robots are equipped with a camera mounted to the robot, providing a first-person view of the environment to the user. The use of a VR environment has some advantages over traditional telepresence interfaces as the incoming video stream from the robot can be displayed in an HMD instead of a screen or tablet. In terms of user comfort, an HMD can show the video feed and the P300 controller regardless of the user's head orientation, which makes smart-home environments more accessible to patients who find sitting upright difficult. This is especially relevant for ALS patients, as sitting up to look at a screen can cause fatigue and discomfort (Sahal et al., 2021). Another benefit of using a VR simulation is that an entire smart home environment, including interactions with appliances and visual feedback, can be simulated in a life-like manner without the need for any additional technology or development. This allows rapid prototyping, user evaluation, and customization at a low cost (Holzner et al., 2009), which is important because the success of a smart home system depends on its ability to meet user needs.

While BCI-driven robot-assisted smart homes show promise in a lab setting, more work is needed to establish their application in a real-life situation for disabled patients. One of the main limitations of the current prototype (and P300 BCIs in general) is the trade-off that exists between the system's classification speed and its accuracy. The number of flash sequences needed for the P300 controller to accurately isolate the intended command limits how fast the system can respond. Our pilot study with one trained user showed that 5 flashes are sufficient for the system to accurately identify the target commands. Improving speed while maintaining accuracy is particularly important for robot navigation and control, as slow response times could make the robot inefficient and prone to accidents. A previous study using a similar setup with a VR headset and the visual P300 paradigm demonstrated that healthy users can reach an average accuracy of 96% with three flash sequences and that depending on the user, spelling with only one flash sequence is possible (Käthner et al., 2015). Such potentially high information transfer rate in P300 BCIs is promising for robot navigation and control in real time, however further user evaluation is needed to confirm this expectation using our proposed prototype.

It is particularly important to test the robot functionalities in a physical environment where enhanced navigation and obstacle avoidance are necessary. Additionally, potential end-users should be included as early as possible in the development process in a user-centered design approach to ensure that the developed functionalities are in line with what disabled users and their caretakers find comfortable and useful (Rogers et al., 2021). Previous research indicates that 84% of ALS patients would be interested in using BCI assistive technology with a non-invasive electrode cap (Huggins et al., 2011). Other surveys attempted to determine the BCI functionalities that would benefit patients the most (Huggins et al., 2011; Olsson et al., 2010). However, as these studies were not geared towards smart homes, further user evaluations are required to identify the limitations of the proposed solution before it is used in practice.

Future studies should outline the possible functionalities of a robot-assisted smart home based on user needs and priorities e.g., by conducting a survey similar to Huggins et al. Huggins et al. (2011). Additionally, simultaneous decoding of multiple EEG features through Hybrid BCI methods or

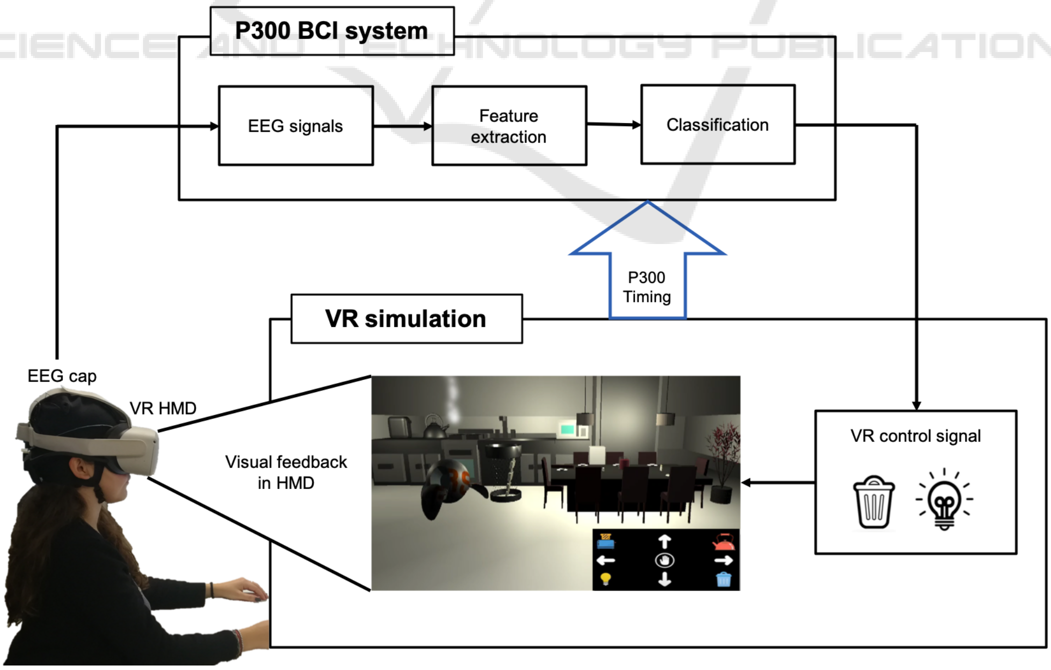


Figure 4: System architecture. The user is instructed to selectively look at one of the blinking icons in the P300 controller board presented at the bottom corner of the VR visual field. The BCI system then predicts the user's selected command based on the P300 response in the EEG signals and subsequently sends a control signal to the VR simulation. This activates the corresponding appliance or the robot in the VR environment, which serves as visual feedback to the user.

novel BCI paradigms such as inner speech classification (van den Berg et al., 2021) could be employed to increase the system accuracy, number of the control commands, and ease of use for the user (Hong and Khan, 2017). For instance, the motor imagery paradigm can be integrated as a more intuitive method for navigation (Su et al., 2011) or the P300 paradigm can be paired with gaze or attention tracking as an on/off switch for active/passive control of the interface (Alimardani and Hiraki, 2020). Such a multimodal interface will enable asynchronous communication with the BCI system whenever the user intends to interact with the environment, which would in return reduce visual strain from the continuous flashing of the stimuli.

In sum, robot-assisted smart home systems that focus on the needs of disabled patients could improve their quality of life and reduce their reliance on caretakers, which is beneficial in both healthcare and private home care settings. A VR simulation allows researchers to fully consider all aspects of the user experience before committing to development phases and to ensure that the potential user groups can benefit from the system in the long term. While more user research, prototyping, and testing are still needed, our application demonstrates the first steps of this process as a proof of concept.

# 4 CONCLUSION

In this paper, we presented a proof of concept for a BCI-controlled robot assistant in a VR-based smart home that enables patients with motor impairment to conduct complex tasks such as object manipulation and environment control. Our solution integrated a VR environment with a P300 BCI system through a custom-designed controller interface; it demonstrated that BCI commands issued via a custom-designed household-oriented P300 interface can be sufficient to control a combination of smart home appliances and an assistive robot. This combination serves as an affordable platform for evaluation and design of real smart home environments for disabled patients. Further developments in BCI hardware/software, robotics, and VR input methods are required to realize automated assisted living systems efficiently.

# REFERENCES

Abiri, R., Borhani, S., Sellers, E. W., Jiang, Y., and Zhao, X. (2019). A comprehensive review of eeg-based brain-computer interface paradigms. *Journal of neural engineering*, 16.

Alimardani, M. and Hiraki, K. (2020). Passive brain-computer interfaces for enhanced human-robot interaction. *Frontiers in Robotics and AI*, 7.

Alimardani, M., Nishio, S., and Ishiguro, H. (2013). Humanlike robot hands controlled by brain activity arouse illusion of ownership in operators. *Scientific reports*, 3:2396.

Demon, R. (2020). Robot sphere. https://assetstore.unity.com/packages/3d/characters/robots/robot-sphere-136226.

Do, H. M., Pham, M., Sheng, W., Yang, D., and Liu, M. (2018). Rish: A robot-integrated smart home for elderly care. *Robotics and Autonomous Systems*, 101:74–92.

Edlinger, G. and Guger, C. (2011). Social environments, mixed communication and goal-oriented control application using a brain-computer interface.

Edlinger, G., Holzner, C., Groenegress, C., Guger, C., and Slater, M. (2009). Goal-oriented control with brain-computer interface. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 5638 LNAI:732–740.

Fazel-Rezai, R., Allison, B. Z., Guger, C., Sellers, E. W., Kleih, S. C., and Kübler, A. (2012). P300 brain computer interface: Current challenges and emerging trends. *Frontiers in Neuroengineering*, 0:1–30.

Guger, C., Daban, S., Sellers, E., Holzner, C., Krausz, G., Carabalona, R., Gramatica, F., and Edlinger, G. (2009). How many people are able to control a p300-based brain-computer interface (bci)? *Neuroscience Letters*, 462:94–98.

Holzner, C., Guger, C., Edlinger, G., Gronegress, C., and Slater, M. (2009). Virtual smart home controlled by thoughts. *2009 18th IEEE International Workshops on Enabling Technologies: Infrastructures for Collaborative Enterprises*, pages 236–239.

Hong, K.-S. and Khan, M. J. (2017). Hybrid brain–computer interface techniques for improved classification accuracy and increased number of commands: a review. *Frontiers in neurorobotics*, 11:35.

Huggins, J. E., Wren, P. A., and Gruis, K. L. (2011). What would brain-computer interface users want? opinions and priorities of potential users with amyotrophic lateral sclerosis. *Amyotrophic Lateral Sclerosis*, 12:318–324.

Hung, L., Gregorio, M., Mann, J., Wallsworth, C., Horne, N., Berndt, A., Liu, C., Woldum, E., Au-Yeung, A., and Chaudhury, H. (2021). Exploring the perceptions of people with dementia about the social robot paro in a hospital setting. *Dementia*, 20.

Koceski, S. and Koceska, N. (2016). Evaluation of an assistive telepresence robot for elderly healthcare. *Journal of Medical Systems*, 40:121.

Käthner, I., Kübler, A., and Halder, S. (2015). Rapid p300 brain-computer interface communication with a head-mounted display. *Frontiers in Neuroscience*, 9.

Luria, M., Hoffman, G., and Zuckerman, O. (2017). Comparing social robot, screen and voice interfaces for smart-home control. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 580–628.

Mattout, J., Perrin, M., Bertrand, O., and Maby, E. (2015). Improving bci performance through co-adaptation: Applications to the p300-speller. *Annals of Physical and Rehabilitation Medicine*, 58:23–28.

Moyle, W., Arnautovska, U., Ownsworth, T., and Jones, C. (2017). Potential of telepresence robots to enhance social connectedness in older adults with dementia: An integrative review of feasibility.

Moyle, W., Jones, C., Dwan, T., Ownsworth, T., and Sung, B. (2019). Using telepresence for social connection: views of older people with dementia, families, and health professionals from a mixed methods pilot study. *Aging and Mental Health*, 23:1643–1650.

Niemelä, M., van Aerschot, L., Tammela, A., Aaltonen, I., and Lammi, H. (2021). Towards ethical guidelines of using telepresence robots in residential care. *International Journal of Social Robotics*, 13:431–439.

Odekerken-Schröder, G., Mele, C., Russo-Spena, T., Mahr, D., and Ruggiero, A. (2020). Mitigating loneliness with companion robots in the covid-19 pandemic and beyond: an integrative framework and research agenda. *Journal of Service Management*, 31:1149–1162.

Olsson, A. G., Markhede, I., Strang, S., and Persson, L. I. (2010). Differences in quality of life modalities give rise to needs of individual support in patients with als and their next of kin. *Palliative & Supportive Care*, 8:75–82.

Q! Dev (2018). Too many items: Kitchen props. https://assetstore.unity.com/packages/3d/props/too-many-items-kitchen-props-127635.

Rogers, W., Kadylak, T., and Bayles, M. (2021). Maximizing the benefits of participatory design for human–robot interaction research with older adults. *Human Factors*.

Rubens, R. (2017). Trash bin. https://assetstore.unity.com/packages/3d/props/furniture/trash-bin-96670.

Sahal, M., Dryden, E., Halac, M., Feldman, S., Heiman-Patterson, T., and Ayaz, H. (2021). Augmented reality integrated brain computer interface for smart home control. *International Conference on Applied Human Factors and Ergonomics*, pages 89–97.

Spataro, R., Chella, A., Allison, B., Giardina, M., Sorbello, R., Tramonte, S., Guger, C., and Bella, V. L. (2017). Reaching and grasping a glass of water by locked-in als patients through a bci-controlled humanoid robot. *Frontiers in Human Neuroscience*, 11.

Studio, A. (2021). Polygon dining room. https://assetstore.unity.com/packages/3d/props/interior/polygon-dining-room-199435.

Su, Y., Qi, Y., Luo, J. X., Wu, B., Yang, F., Li, Y., Zhuang, Y. T., Zheng, X. X., and Chen, W. D. (2011). A hybrid brain-computer interface control strategy in a virtual environment. *Journal of Zhejiang University SCIENCE C 2011 12:5*, 12:351–361.

van den Berg, B., van Donkelaar, S., and Alimardani, M. (2021). Inner speech classification using eeg signals: A deep learning approach. *2021 IEEE 2nd International Conference on Human-Machine Systems (ICHMS)*, pages 1–4.

Watson, G. S., Papelis, Y. E., and Hicks, K. C. (2016). Simulation-based environment for the eye-tracking control of tele-operated mobile robots.

Wiese, E., Metta, G., and Wykowska, A. (2017). Robots as intentional agents: Using neuroscientific methods to make robots appear more social.

Wilson, G., Pereyda, C., Raghunath, N., de la Cruz, G., Goel, S., Nesaei, S., Minor, B., Schmitter-Edgecombe, M., Taylor, M. E., and Cook, D. J. (2019). Robot-enabled support of daily activities in smart home environments. *Cognitive Systems Research*, 54:258–272.

Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., and Vaughan, T. M. (2002). Brain–computer interfaces for communication and control. *Clinical Neurophysiology*, 113:767–791.

Zhang, G. and Hansen, J. P. (2020). People with motor disabilities using gaze to control telerobots. *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*.