User Modeling and User-Adapted Interaction (2023) 33:405–440
https://doi.org/10.1007/s11257-022-09333-y

Personalized home-care support for the elderly: a field experience with a social robot at home

Claudia Di Napoli[1] · **Giovanni Ercolano**[2] · **Silvia Rossi**[2]

Received: 4 March 2021 / Accepted in revised form: 29 May 2022 / Published online: 23 June 2022

Abstract

Socially assistive robotics (SAR) is getting a lot of attention for its potential in assisting elderly users. However, for robotic assistive applications to be effective, they need to satisfy the particular needs of each user and be well perceived. For this purpose, a personalization based on user's characteristics such as personality and cognitive profile, and their dynamic changes is a crucial factor. Moreover, most of the existing solutions rely on the availability of specific technological infrastructures, generally requiring high economic investment, and that cannot be easily placed in different environments. Personalization and adaptation of assistive robotics applications to different user's characteristics and needs, and even to different technological environments, are still not fully addressed in real environments. In the present work, the results of the UPA4SAR project are presented. The project aimed at providing a social robotic system to deliver assistive tasks for home care of patients with mild cognitive impairment in a personalized and adaptive way. We introduce the general architecture of the system and the developed robotic behaviors. Personalization and dynamic adaptation of assistive tasks are realized using a service-oriented approach by taking into account both user's characteristics and environmental dynamic conditions. Field experimentation of the project was carried out with 7 patients, using the robotic system autonomously running in their homes for a total of 118 days. Results showed a reliable functioning

This study was funded by MIUR (Italian Ministry of Education, Universities, and Research) within the PRIN2015 research project UPA4SAR—User-centered Profiling and Adaptation for Socially Assistive Robotics (Grant n. 2015KBL78T). The authors thank OMITECH s.r.l. for providing the robots used in the experimentation.

✉ Silvia Rossi
silvia.rossi@unina.it

Claudia Di Napoli
claudia.dinapoli@cnr.it

1 Institute for High Performance Computing and Networking, CNR, Naples, Italy

2 Department of Electrical Engineering and Information Technologies, University of Naples Federico II, Naples, Italy

of the proposed robotic system, a generally positive reaction, and a good acceptability rate from patients.

Keywords Social assistive robotics · User profiling for HRI · Personalization for HRI · Service-oriented robotics · Field experimentation

1 Introduction

Assistive Robotics and Socially Assistive Robotics (SAR) are nowadays receiving a lot of attention from the scientific and technological communities for their potential impact on improving the quality of life of elderly people. An improvement in their autonomy would allow them to stay for longer in their homes and to alleviate the burden on caregivers and family members. This is even more crucial when they are affected by neurological disorders, such as Alzheimer's disease characterized by a decline in cognitive functions and memory loss, as well as mild cognitive impairments (MCI) that have an impact on the performance in conducting daily living activities (Chiaravalloti and Goverover 2016). Applications of SAR in this domain as patient monitoring to provide information about the patient's daily life, alerts for possible anomalies (Do et al. 2018), cognitive stimuli, and reminders to limit cognitive reserve with its consequences, are crucial. First of all, assistive applications depend on the user's clinical needs. The typical approach for the development of a care protocol, i.e., a sequence of assistive tasks, requires the intervention of an expert to manually accommodate the different needs of each user through software updates (Gu et al. 2020). This limits the possibility to deploy an effective assistive application for different patients, requiring continuous intervention, while their assistive requirements change. To address these limitations, assistive application design should allow for easy personalization of the system functionality to different contexts, technology availability, and users' clinical needs. Moreover, to effectively use robotic systems in domestic environments, it is necessary to work on reducing their cost, but also on increasing the reliability and robustness of the developed devices (Francillette et al. 2020). Reliability is typically obtained by endowing the environments with different sensors and supporting devices that require costly, and sometimes invasive, modifications of the environment. As a consequence, testing of these systems relies on the availability of controlled environments, such as laboratories or retirement houses, while field experimentation is deemed to properly assess the benefits and acceptance of such technologies. Robotic systems deployment should not be dependent on specific hardware installations in environments with their specific characteristics and structural limitations, to adapt to different technological contexts. Secondly, to be widely accepted, users must experience the utility of the system and the easiness of use in interacting with the robot (Ghafurian et al. 2021; Casey et al. 2016; Koh et al. 2021) while limiting the feeling of intrusiveness that the continuous use of monitoring devices may involve (Cavallo et al. 2018). This requires the personalization of the robotic system interactions to each patient profile to increase its acceptance. It has been shown that personalization to the specific needs of an elderly adult, especially in cases of vulnerability and cognitive impairments, has an impact on technology acceptance (Moro et al. 2018). Typical approaches to SAR development address the problem with ad-hoc manual creation of robot behaviors for the general needs of the considered population (Tapus et al. 2007), without addressing the personalization of the interaction with technological devices to individual patients' needs, preferences, and profile.

Adaptation is another essential feature of any interaction with a non-human device. Patterns of adaptation that can be considered when interacting with virtual human-like entities with communicative and emotional capabilities concern a behavioral level, a conversational level, and a signal level (Biancardi et al. 2021). Various SAR systems have been designed with a user-specific adaptation mechanism in different application domains (healthcare and therapy, education, work environment, and public spaces), and with different adaptation features. They are based on understanding emotions, communicating with high-level dialogue, learning/adapting according to user responses, establishing a social relationship, and reacting to different social situations (Ahmad et al. 2017). Less work has been reported on adaptive social robots that can modify their behavior in settings characterized by a short-term adaptation in human–robot interaction (Andriella et al. 2020), i.e., settings where the user does not have any training on how to interact with the robot and he/she is not fully aware of the robot capabilities, as in our case, so learning approaches are not adopted to adapt the robotic behavior.

This paper presents the results of the Italian research project UPA4SAR—User Profiling and Adaptation for Socially Assistive Robotics—which aimed at the development and deployment of a well-accepted assistive system for home care of patients with neurological impairments. The system is based on a mobile social robot capable of delivering personalized assistive services. We report on how personalization and adaptation are addressed in terms of functional and non-functional requirements of the assistive robotic application and how these requirements are mapped to a service-oriented approach to tailoring the assistive application for every single user. In detail, we focus on the user and technological personalization and adaptation. The first accounts for the possibility to personalize the robot assistance behavior in terms of delivered assistive tasks (what), the time to be executed (when), the mode they are executed with (how), the entertainment contents, and to adapt them in case dynamic events occur. The second accounts for the possibility to select the devices delivering assistive services depending on the equipment of the home environment and changing them on the fly if more devices are available to deliver the same service.

The results of a field study running from July 2019 to January 2020 are presented. The study involved 7 patients (average age 72 years, 1 patient with Alzheimer's disease, 4 with mild cognitive impairment, and 2 with subjective memory impairment) that experimented with the system autonomously running in their homes for an average of 16 days each, without the need of supervision of technical help. For each patient, we evaluate the experience in terms of the perceived usefulness and acceptability by relying on the analysis of interviews conducted before and after the experiments. We also collected feelings and emotions during the experimentation using a daily visual mood scale and interviews on-site or over the telephone. Moreover, technical aspects related to the practical suitability, technology readiness, and robustness of the system are evaluated. According to (Martins et al. 2019), while in HCI personalization and adaptation techniques are mature and they lead to high Technology Readiness Levels

(TRL), in HRI these values are still very low (from 4 to 5). Hence, the challenges and opportunities gathered from the reported field experimentation in the context of an easily deployable, low-cost, and fully autonomous robotic system represent a step forward in the HRI field.

2 Related works

In the last decade, several projects have been funded and different robotics devices investigated to be used in elderly assistive settings. A recent systematic review on the use of social robots for the care of patients with dementia and their evaluation by caregivers is reported in (Ghafurian et al. 2021). The review covered a range of robots with different levels of autonomy (e.g., from teleoperated robots that were fully controlled by another person to robots that were designed to work autonomously). The robots considered in the study had different assistive objectives, such as connecting a patient with family members that were physically away, providing companionship, promoting health or therapeutic support, and helping with completing daily tasks (Saunders et al. 2016; Bonaccorsi et al. 2016; Fischinger et al. 2016; Portugal et al. 2019). Among the issues reported in the analysis, the necessity of having systems that are easy to use emerged (e.g., in learning how to interact with it with respect to other devices). Indeed, using an assistive robot typically requires more maintenance effort as compared to other types of intelligent systems, such as virtual assistants. Further, the robustness and reliability of robots are shown to affect caregivers' perception of the usefulness of the robot. To accomplish these goals, robot technologies for sophisticated perception, natural interaction, and autonomous navigation, as well as for monitoring and localization are needed. This implies the development of robotic systems with high costs not easily affordable in a private home environment.

In the "Accompany" project (Saunders et al. 2016), the Care-O-Bot 3 was developed for complex interactions with elderly people, providing services to facilitate independent living at home, and assisting the user in the daily tasks. The authors proposed an ontology for the robotic home, consisting of sensors, locations, objects, people, the robot, and the robot's behaviors. The house is equipped with about 50 additional sensors, including cameras mounted on the ceiling. Hence, the system requires expensive home automation with an expensive robot that cannot be available in any environment. This project allows for manual customization/selection of the robot behaviors by both experts and non-experts, via simple interfaces. Even the elderly person can issue commands via the tablet. However, there is no mention of clinical planning of elderly care activities.

The need for an ontological approach to domain representation is also explored in (Umbrico et al. 2020). This paper proposes a cognitive approach integrating ontology-based knowledge reasoning, automated planning, and execution technologies. The envisioned approach aims at providing a socially assistive robotic system with the capability to autonomously identify the set of assistive services that are needed in a given scenario. Moreover, it aims at scheduling the needed services to guarantee continuous assistance during daily home living and to decide how to execute these services according to the profile of the user. Automated planning techniques for the administration of personalized and adaptive reminders were realized in the context of the Giraff+ project relying on a fully teleoperated (non-autonomous) robot (De Benedictis et al. 2015). However, only the feasibility of personalization and adaptation attainable with an ontological approach is discussed, and real experimentation has not been carried out as in our case.

In the “CompanionAble” project (Schroeter et al. 2013), services provided by the robot include reminders of appointments, predefined or added by the user or caregiver, frequent recommendations for specific activities provided by the caregiver, video calls with family and friends, and cognitive stimulation games to monitor cognitive decline. In addition, the robot can be controlled either via displays located in the smart environment or via voice commands. Volunteers tested the system by freely using the robot for two days. On the contrary, our project does not rely on specific IoT devices for smart homes to limit both the cost of the platform and their invasiveness, and the system was used for longer in real home environments.

The robotic application developed for the “Hobbit” project (Fischinger et al. 2016) aimed at manipulating objects but also providing entertainment functionalities, such as games, exercise, films, music, and books to keep the user cognitively and physically active. The application design allows for basic robot customization through user choice of sound volume, robot speed, and robot voice gender, but does not allow for more advanced customization on the schedule and the type of assistive services offered by the robot.

A modular approach for the development of assistive behaviors was considered in the “Robot-Era” project (Bonaccorsi et al. 2016). The project proposes the use of cloud systems for service delivery and the use of sensors to locate the person in the apartment, such as mobile radios worn by the users. While a service-oriented architecture was embraced as in our project, our platform does not rely on costly robotic devices and extensive use of ambient sensors for user localization and monitoring.

The “SocialRobot” project is the more similar to ours (Portugal et al. 2019). In this project, researchers developed their mobile robotic platform consisting of a modular system to support caregivers, family members, and friends, helping the elderly during their daily tasks, while we used an off-the-shelf low-cost robotic solution. Similar to our project, they adopted a service-oriented approach proposing a platform that does not involve modifying the environment or adding smart devices and monitoring sensors to the environment. In “SocialRobot,” the adaptation of human–robot interactions is achieved through emotion recognition and empathic interaction. Through a web interface, caregivers can manage the user profiles and edit the personalization features, such as the patient agenda, medicine, and favorite activities. Hence personalization is realized using a web-based virtual collaborative social community network that enables the effective administration and coordination of the user profiles and assistance of the elderly person. On the contrary, in our approach, personalization and adaptation are addressed in terms of functional and non-functional requirements mapped to service-oriented assistive tasks to tailor their provision for every single user’s characteristics and environment. Finally, in the “SocialRobot” project, the robot was tested only in a care center during a week-long pilot study focusing on the evaluation of security, autonomy, privacy, and safety. In our case, the system operated in private houses without any remote intervention with a focus on robot acceptance. Indeed, another important issue in HRI is the necessity of experimentation in the field and uncontrolled settings such as home environments.

In the "MARIO" project (Casey et al. 2016), a robot was developed to promote social connection and reduce loneliness and isolation by providing Patients with Dementia (PwD) access to several applications via speech and/or touchscreen commands. MARIO was developed, tested, and evaluated in a long-stay residential setting over 13 months. The important result of the experimentation, conducted in the real setting and including the views of people with dementia, was that robots are acceptable for this class of users, so strengthening the claim that social robots are acceptable for dementia care. However, residential settings are still more controlled environments with respect to private houses.

Personalized and adaptive interaction with a robot strongly relies on the availability of a model of the user, and the integration of this model in the decision-making algorithms of the robot. But user modeling and profiling techniques in robotics are still at an early stage. According to Martins et al. (2019), personality traits and their use in HRI personalization still constitute a research gap. When the interaction requires the robot to move in the surrounding space (Nikolaidis et al. 2015), the user's preferences concerning only proxemics (Rossi et al. 2017) and the legibility of trajectories are considered (Cakmak et al. 2011). While the use of stereotypes (Wagner 2015), in the form of personas, is nowadays quite typical in HRI when dealing with cognitive disabilities, the individual differences between subjects are still considerable and relevant, so requiring a user-based profiling process. For example, in (Duque et al. 2013), users' profile variables were identified to provide different personas in terms of the user gender, educational level, technical background, computer experience, previous experience and attitude toward robots, users' personality traits, and the robot's role (e.g., companion, tutor, and so on). However, once having this information about the user, the robot's behavior adaptation should not be hard-coded for these features, but they should be treated as parameters to adapt interaction on a single user case-based, as in our case. Moreover, both static parameters such as gender and personality, and dynamic parameters, such as changes in psychological distress, engagement, and distraction should be considered (Rossi et al. 2018).

The social component of the interaction with a robot was considered in (De Carolis et al. 2017) whose approach requires the development of user models that involve reasoning on cognitive and affective components of the user's state of mind. The user model is obtained from the experience of human caregivers and knowledge about the role of empathy in assisting elderly people to make the robot's behavior believable. In our approach, we did not focus on achieving a robotic emphatic behavior.

Finally, in the context of assisting dementia patients, some works propose the use of the ICF framework (International Classification of Functioning, Disability and Health) to build user profiles and personalized assistance. This standard framework seems quite useful to represent different aspects (e.g., physical and cognitive) that may characterize the state of a user (Umbrico et al. 2020; Kostavelis et al. 2019; Filippeschi et al. 2018; García-Betances et al. 2016). In our work, we are not dealing with detailed modeling of physical/cognitive impairments since the assistive requirements are directly provided by the patient's doctors and caregivers. Adaptation is focalized on some user's characteristics also considered in the ICF.

3 Personalization requirements for assistive robotic applications

To address the different types of personalization and adaptation of the SAR application, due to the variability of every single user and each home environment, we defined a set of *functional* and *non-functional* requirements. They take into account the user's daily needs, the interaction modality with the robot and other devices, and the availability of technological devices. The elderly with cognitive impairments have specific needs and characteristics depending on their personal cognitive, emotional, psychological status, and cultural background not always easily modeled according to well-defined classifications. In the same way, differently from hospitals or nursing homes, home environments are characterized by specific structural characteristics, space, and network connectivity features.

3.1 Functional requirements

In a recent study (Johnson et al. 2020), functional requirements expressed by the elderly, clinicians, and caregivers for developing an affordable mobile robot are presented. The survey identified thirty-six priority tasks, and among these, the most important tasks desired by seniors in a low-cost robot concern the possibility to be helped in their daily living activities, be entertained with leisure activities, have a customized interaction, and the ability to socialize with others. In contrast, clinicians and caregivers prioritized tasks to remind care plans and monitor the health and safety of the elderly. Moreover, the robot's autonomous monitoring activities, where the user is only a passive agent, may not be perceived as useful, and considered intrusive, while non-personalized reminders may annoy the patient. Hence, while the plan of assistive functionalities of the robot has to be provided by clinicians, user requirements should be taken into account, and entertainment activities should be provided not only to limit cognitive reserve but also to make the robot system more valuable. Ad hoc designed technologies providing a one for all solution now available on the market are not a complete answer to the different and changing needs of this class of users.

A set of *functional requirements* to take into account the home robotic assistance functionalities coming from the user's clinical needs are identified. They concern:

- The definition of assistive functionalities necessary to meet the patient monitoring and medical treatment needs, together with entertainment and cognitive activities;
- The guarantee that assistive functionalities are delivered in compliance with the time requirements of each user;
- The easy adaptation of the delivered assistive functionalities when changes occur because of the new patient's needs.

To meet these requirements, it is fundamental to collect as much information as possible from different actors, such as patients, physicians, neuropsychologists, family members, and caregivers to compile an added value personal daily assistive plan including the necessary assistive functionalities based on their daily needs, their medication requirements, and the schedule of their activities.

3.2 Non-functional requirements

Personalization and adaptation of robotics-based home-care applications depend on the available technological environment, and the modes the assistive application is delivered for each user, and, as such, they are related to non-functional requirements. Regarding the technological environment and performance of assistive tasks, reliability is the first requirement. To be effectively deployed and tested, the robot has to be fully autonomous in its operations. The reliability of robotic operations may be enhanced by the use of supporting technology and sensors to be deployed in the environment, so creating an ambient assistive living space. Nevertheless, a low-cost approach requires trade-offs in the use of different technologies in private homes (Moyle et al. 2018).

The identified non-functional requirements are split into two categories. The first is *environmental non-functional requirements* as follows:

- The adoption of affordable but still sufficiently reliable technology that can be made easily available in home environments, so a wide penetration of technology is guaranteed;
- No tight coupling of the provided functionalities to the available technology, to manage both technology evolution and/or technology unavailability;
- Heavy structural intervention in home environments that may be costly and not well perceived by the elderly should be avoided;
- Remote control of technological devices and dependence on internet connection should be avoided as much as possible to guarantee the autonomous functioning of the assistive application;
- Easy deployment of both the application and the required technological devices in the home environments.

Regarding the user perception of assistive tasks, personalization of the interaction with the technology is a key requirement to achieve the possibility of long-term adoption of companion robots (Castellano et al. 2008). Elderly users prefer to interact with adaptive systems (Heerink et al. 2010) that perform tasks not only correctly and efficiently, but also in an acceptable manner according to their individual preferences (Karami et al. 2013). So, when interacting with a robot, personalization is related both to the type of necessary assistive actions to be provided, and to *how* these actions are provided in terms of usefulness, satisfaction, intrusiveness, and privacy (Di Napoli and Rossi 2019).

To take into account perceived usefulness, and satisfaction, while limiting intrusiveness, a set of additional *user-centric non-functional requirements* for personalizing the assistive application is identified:

- Physical, cognitive, and social interaction with the robot, should be personalized taking into account the user profile;
- In the case different devices providing the same functionality with different delivering modalities are available, the one better matching the user profile should be selected;
- When providing entertainment activities, user modeling and recommendation techniques should be deployed to suggest them according to the user preferences;

- Both the assistive plan and the interactions with the robot should be adapted to changes that may occur in the patient's state during the assistance period.

4 System design for functional and non-functional requirements

To take into account both functional and non-functional requirements, the assistive robotic application has been conceived according to a *service-oriented* approach (Wu et al. 2015). It allows for clearly separating the functional and non-functional properties of a software system through the *service abstraction*. In particular, functional properties of a service concern the actual implementation of a given functionality and the necessary technical information to interact with it: the provider, communication protocols, invocation address, and input and output formats. Non-functional properties of a service define how the functionality operates, i.e., its Quality of Service (QoS) properties referring to the set of characteristics a functionality can be delivered with. In addition, the service abstraction allows decoupling the description of a functionality delivered by a service and its QoS parameters from the actual implementation. The implementation is platform-dependent, but since it relies on standardized web service technology to interoperate with other services, platform dependence does not affect the design and the operation of the assistive application.

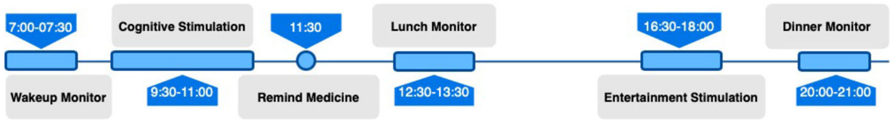
According to the proposed service-oriented approach, the robotic home-care assistance is designed as an *Assistive Daily Plan* that is a collection of independent and autonomous *Assistive Tasks*. Assistive tasks are represented as a composition of *Services* that can be delivered by the robot or other devices.

In our approach, the identified functional requirements refer to the functional properties defined at the level of the assistive daily plan. It refers to the types and the timing of the assistive needs of the users derived by analyzing the activities they usually perform at their home during the day, i.e., their daily routine. The identified non-functional requirements refer to non-functional properties defined at the level of the assistive daily plan, the single assistive tasks, and the single services composing each task. Both functional and non-functional properties are used for personalizing the daily assistive plan according to the specific user profile and available devices, and for its adaptation when changes in both the assistive environment and the user profile occur.

The identified types of assistive tasks are:

- *Monitoring tasks* to monitor some activity of daily living, e.g., having lunch, having dinner;
- *Cognitive and Entertainment tasks* to suggest cognitive and entertainment activities such as playing cards and mind-training exercises, watching a leisure video, listening to music, or watching an informative video;
- *Reminder tasks* to remind critical activities such as taking medications.

The types and the schedule of assistive tasks are extracted from the user's daily routine, so forming a personal daily assistive plan (an example is reported in Fig. 1).



Time Range	Assistive Task	Description
07:00-07:30	Wakeup Monitor	Monitor the user woke up
09:30-11:00	Cognitive Stimulation	Suggest the user a cognitive activity
11:30	Remind Medicine	Remind the user to take the planned medicine
12:30-13:30	Lunch Monitor	Monitor the user is having lunch
16:30-18:00	Entertainment Stim.	Suggest the user an entertainment activity
20:00-21:00	Dinner Monitor	Monitor the user is having dinner

Fig. 1 An example of a daily assistive plan

4.1 User data

To personalize the daily assistive plan for each user, detailed personal information should be collected. In the UPA4SAR project, the neurologist team ran cognitive tests to provide the patient cognitive profile according to the CDR scale (Morris 1993) (very mild, mild, moderate, and severe dementia). Regarding CDR values, only three intervals were considered (no dementia (CDR = 0), MCI (CDR = 0.5/1), and moderate cognitive impairment (CDR = 2)). Patients with severe cognitive impairment (CDR = 3) were not considered.

Neurologists were also responsible to collect information about users' routines, their medication therapy plans, and their entertainment needs through interviews with family members or caregivers and the patients. This information is organized in the form of the patient daily routine, to determine the assistive tasks to be performed by the robot. Finally, they provided users personal data including their education level, in terms of the number of years of education, and their entertainment preferences.

The psychologist team ran personality tests to provide the personality profile of each patient according to the Neo Personality Inventory 3 test (Neo-Pi-3) (McCrae et al. 2005) measuring five personality traits (Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness). Only Neuroticism and Openness were included in the personality profile as the traits impacting the interaction with the robot and the technology acceptance. The other personality traits such as extraversion, agreeableness, and conscientiousness, were not sufficiently supported by literature findings to provide clear suggestions in the application context. For the personality profile, each user is profiled as having a *Low* or *High* value of the considered traits according to the two intervals provided by the psychologists.

To help neurologists and psychologists to provide this information, structured web-based forms were provided. All collected information is structured in XML formats and automatically translated into a relational database representing the static user's profiling data, as reported in Fig. 2. In addition, dynamic profiling data resulting either from monitoring tasks or from human monitoring are registered in the database as Daily Observations.

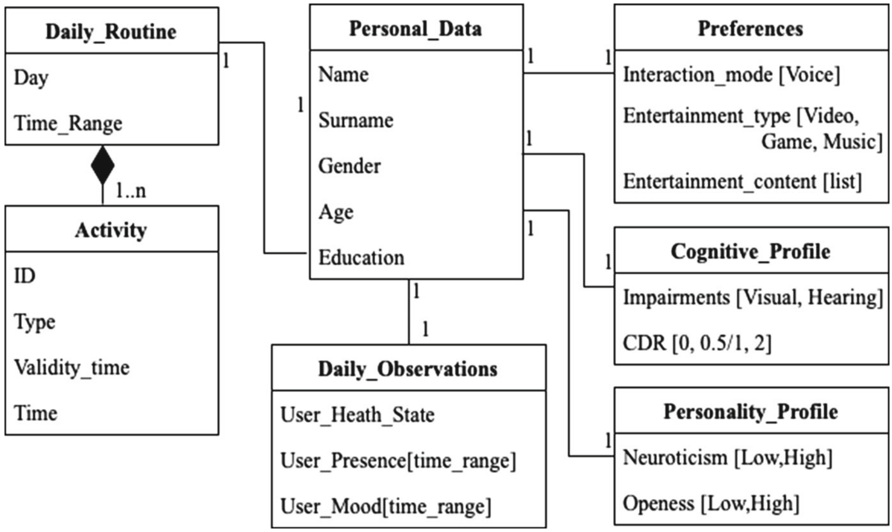


Fig. 2 Profiling data collected for the patients

4.2 Service-oriented daily assistive plans

A daily assistive plan is a sequence of assistive tasks characterized by a set of functional attributes that are the daily duration, the number, and the types of the component assistive tasks.

According to the service-oriented approach, each assistive task is a composition of sub-functionalities needed to accomplish it. It is represented by a so-called *Abstract Workflow* (Di Napoli et al. 2017) that is an oriented graph whose nodes represent the sub-functionalities and arcs their execution dependencies. Each assistive task is characterized by a set of functional attributes that are the daytime when its execution is scheduled, and the time range the assistive task may take place, according to the user's daily routine. Each sub-functionality is represented by an *Abstract Service* that is an atomic functionality, i.e., a self-contained functionality that can be delivered by a device. The definition of a sub-task in an abstract way allows selecting the suitable actual service implementation available to provide it, at the time it is scheduled for execution. An example of abstract workflow is reported in Fig. 3 for the *Entertainment Stimulation* assistive task.

The actual implementation of an abstract service, called a *Daily Assistive Action*, depends on the specific device providing the corresponding functionality. It relies on standard web service technologies for communication and standard network protocols for their invocation and interoperation with other services. An abstract service can be provided by more than one daily assistive action. Daily assistive actions have non-functional QoS attributes accounting for how the corresponding functionality is delivered (Di Napoli et al. 2018). They depend on the specific device responsible for their execution (Di Napoli and Rossi 2019), and their values are personalized according to the specific user profile. A daily assistive plan for a specific user is a composition

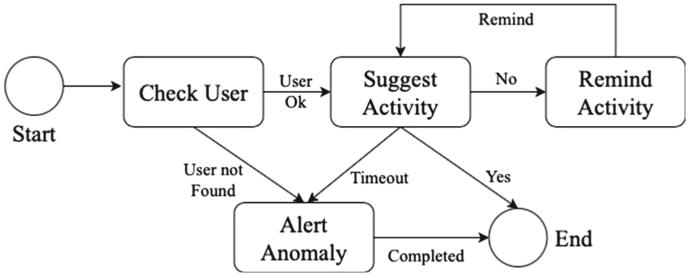


Fig. 3 Abstract workflow for the *Entertainment Stimulation* task

of executable assistive tasks that are obtained starting from the corresponding abstract workflows, by replacing each abstract service with a personalized daily assistive action.

4.3 Daily assistive actions as microservices

Daily assistive actions implementing assistive robot behaviors, as well as perceptual capabilities of the smart environment are provided as *Microservices* (Ercolano et al. 2019). Each microservice may implement a daily assistive action alone or it can be combined with others to provide a more complex functionality that is exposed as an atomic service.

In Table 1, we briefly recap the developed microservices specifying the device providing them and a short description of their functionality. More details on the developed services can be found in (Raggioli and Rossi 2019; Tizzano et al. 2020; Ercolano et al. 2017, 2018, 2019). It should be noted that since no environmental sensors are used to detect the user position or activity, *Find, Look and Approach User* are microservices provided by the robot. In the same way, the *Activity Recognition* microservice is realized by using the robot camera once the user is recognized by the robot (Ercolano and Rossi 2021). Moreover, there are monitoring services whose results are registered in the user profile database as *Daily Observations* to take into account dynamic events impacting the user's state. Examples of these services are *Check*, *Mood Recognition*, and *Activity Recognition*. Due to technology availability, and security concerns, all the daily assistive actions were developed to work offline without requiring an internet connection. Hence, it was not possible to rely on cloud-based services for speech interaction. Indeed, communication between the user and the robot takes place using the tablet that shows robot dialogues via speech and text, while the user can provide input and answers via the tablet touch display.

The QoS attributes of microservices can be static or variable. The former has a single value, like the intrusiveness, and so they cannot be adapted. For these services, personalization relies on the possibility to select the microservice with the QoS static attribute values more suitable to the user's profile in the case more services may provide the same functionality (see for example *InRoomDetection* microservice in Table 1). The latter may have different values for a given QoS attribute, as the proxemics, or interaction modalities. Hence, these are parameters that can be used to personalize a behavior according to the user's profile.

Table 1 A summary of the developed assistive services

Services	Device	Brief Description
Monitoring Services		
HR Detection	Wearable	The smartwatch detects the heart rate of the user for approximately 15 seconds
Pose Detection	Wearable	The smartwatch gathers accelerometer and gyroscope data samples and a Deep Neural Network recognizes and outputs the activity performed
In-Room Detection	Wearable	Distances from the reachable beacons placed in each of the rooms considered are detected
In-Room Detection	Robot	The label associated with the room with the smaller distance is returned. If this service is called after the robot has approached the user, it provides the location of the user
Emotion Recognition	Robot	It recognizes the user's emotions relying on the Affectiva SDK
Mood Recognition	Wearable	It analyzes walking patterns to evaluate the user's mood
Activity Recognition	Robot	The robot's camera records a video of the user. For each frame, the skeleton coordinates of the joints of the user are extracted and a Deep Neural Network is used for activity classification
Navigation Services		
Find Charging Station	Robot	The robot wanders toward the room where the charging station is located (using In Room Detection)
Find User	Robot	The robot wanders while avoiding obstacles for one minute. To find a user, this service has to be combined with the "Look User" service
Look User	Robot	The robot rotates on itself to look for a person. PoseNet is used to check if a person is in the field of view of the robot
Approach User	Robot	It relies on the evaluation of the user pose from his/her skeleton data and on the recognition of a specific user with FaceNet
Interaction Services		
Speech and Utterance	Robot	An utterance is shown on the robot tablet and/or using the robot speech
Check	Robot	An interface with a question and two buttons (for positive and negative answers) is shown on the robot tablet. It is used to implement reminders and to check the health status through a dialogue with the patient
Suggest	Robot	An interface with a suggestion and a button, to check if the user accepts the suggestion, is shown on the robot tablet
Video	Robot	A video is played on the tablet of the robot
Audio	Robot	A list of songs is played by the robot and shown on the tablet
Game	Robot	A cognitive game is shown on the robot tablet
Photos	Robot	The robot takes pictures of the user to populate the dataset of the feature vectors extracted by the FaceNet

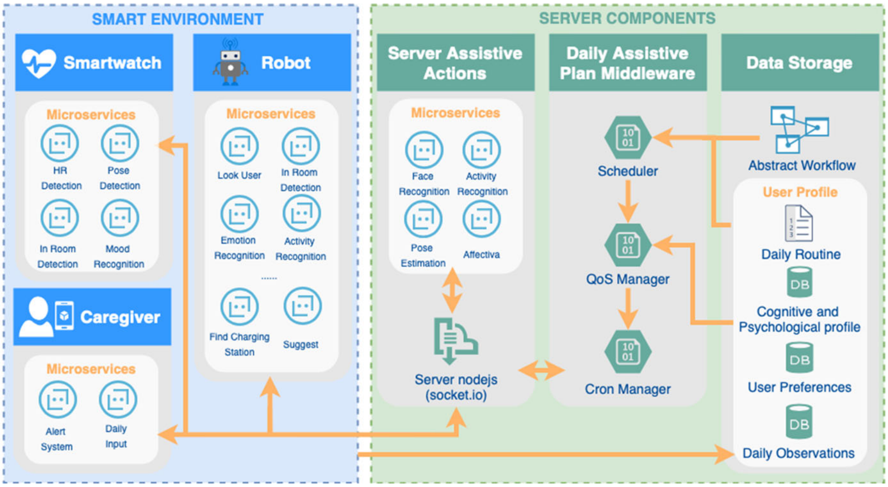


Fig. 4 The architecture of the assistive robotic framework

The architecture of the robotic system for generating and executing assistive tasks starting from the corresponding abstract workflows and the available microservices is reported in Fig. 4. It is composed of the smart environment (blue boxes) including the technological devices and a human caregiver, and of software modules (green boxes) running on a server node. The devices, such as the "Robot," the "Smartwatch," and the other "Server Components," are registered in an application server represented by the "Server nodejs (socket.io)" that exploits the Socket.IO communication library to manage the communication with the client devices.

Additional robotic skills or new functionalities provided by other devices developed by different stakeholders and with different technologies can be added as new daily assistive actions. They can be registered in the application server once agreed external interfaces to bind them to the corresponding abstract services are provided. The interfaces specify their invocation address, the input and output formats, and the communication protocols to be adopted for their invocation and the correct exchange of inputs and outputs, to guarantee their interoperability. Hence, platform dependence is transparent to the robotic application. In our case, we developed daily assistive actions for the robot as Android applications, but the same actions could be implemented using ROS or other robot operating systems.

4.4 Personalization criteria

Daily assistive plans are personalized by taking into account functional and non-functional properties at different levels concerning the daily assistive plan, the single assistive task, and the single services composing an assistive task.

The first level relies on the following functional properties of a daily assistive plan, derived from the user's daily routine:

Table 2 Repetition frequency for the reminder task

CDR	Low Neuroticism	Low Neuroticism
2	5 m	10 m
0.5–1	10 m	20 m
0	15 m	30 m

1. the types of assistive tasks composing the daily assistive plan (i.e., monitoring, entertainment, and reminder);
2. the number of assistive tasks composing the daily assistive plan compliant with the user's daily routine;
3. the time at which assistive tasks are delivered during the day.

The assistive needs of each patient are given by clinicians suggesting the number of entertainment activities. According to their guidelines, the higher the cognitive impairment level is, the higher the number of the suggested entertainment stimulation activities to reduce cognitive reserve is.

The second level relies on the following non-functional properties of a single assistive task:

1. The content type of the suggested entertainment stimulation activity (video, music, game);
2. The repetition frequency at which a reminder task is repeatedly executed in the case of an unsuccessful outcome of the reminder;
3. The repetition frequency at which an entertainment task is repeatedly executed in the case of an unsuccessful outcome of the corresponding entertainment activity;

In detail, the type of suggested entertainment (video, game, music) and the contents are personalized to both the entertainment preferences of the user, but also the age, gender, and education level. The cognitive and personality profiles are used to determine the repetition frequency of reminder assistive tasks in case the user does not perform the reminded activity. According to the guidelines of clinicians, the higher the cognitive impairment level is, the higher the repetition frequency of the reminder assistive task is, since users are more subject to easily forget to perform activities. Moreover, according to the psychologists' guidelines, also the neuroticism personality trait of the user should be considered to personalize the remind frequency value. A high value of the neurotic trait requires a lower reminder frequency to limit discomfort. The two requirements are balanced as reported in Table 2.

The personality profile provides information also to individuate the frequency at which entertainment stimulation activities may be suggested to the user to limit discomfort. As suggested by psychologists, the personality factors that may impact the perception of intrusiveness of the robot are openness and neuroticism. Hence, the frequency at which the robot interacts with the user should be modulated according to the values of these personality factors, to limit a possible aversion to the suggestions. The frequency was set for different classes of users according to their neuroticism and openness personality traits as reported in Table 3 (Di Napoli et al. 2019). All frequency values were determined after an analysis conducted by the project teams

Table 3 Repetition frequency for the *suggest activity* task

Openness	Low neuroticism	Low neuroticism
Low	40 m	60 m
High	20 m	40 m

Table 4 A subset of implemented microservices and their non-functional attributes

Service	Device	Interaction modality
FindUser	Robot	Distance[Near, Medium, Far], Interaction_Mode[GUI, GUI-Voice], Voice[Male, Female], Sound[High, Regular], Led_Lights[Off, On]
ActivityRecognition	Robot	Distance[Near, Medium, Far], Led_Lights[Off, On]
Suggest	Robot	Distance[Near, Medium, Far], Interaction_Mode[GUI, GUI-Voice], Voice[Male, Female], Sound[High, Regular], Led_Lights[Off, On]
ApproachUser	Robot	Distance[Near, Medium, Far]
Check	Robot	Distance[Near, Medium, Far], Interaction_Mode[GUI, GUI-Voice], Voice[Male, Female], Sound[High, Regular], Led_Lights[Off, On]

that observed the reactions of a set of patients carrying out trial sessions with the robot in the controlled environment of the Robotic laboratory of the University of Naples.

The third level of personalization concerns the selection and the interaction modalities of the daily assistive actions represented by their non-functional attributes. Examples of non-functional attribute values of some daily assistive actions are reported in Table 4.

The values of the interaction modalities attributes are set for each user following the profile characteristics that can potentially have an impact on the acceptance of the technology for the considered classes of users (Di Napoli and Rossi 2019). These associations are reported in Table 5.

4.5 The daily assistive plan middleware

The composition, personalization, adaptation, and execution of the assistive plan for each user are managed by the *Daily Assistive Plan Middleware*. It plays the role of a middleware layer between the application layer of daily assistive actions, and the smart environment layer of the technological devices, as reported in Fig. 4. The daily assistive plan middleware is composed of three main components: the *Scheduler*, the *QoS Manager*, and the *Cron Manager*. The scheduler and the QoS manager are responsible to manage user personalization and adaptation by processing, at execution time, the abstract workflows that compose the daily assistive plan for each user.

The scheduler processes information regarding the user's daily routine to determine the schedule, the number, and the types of assistive tasks to be executed every day to compose the daily assistive plan. The number of days the assistance is planned for is set in the configuration files for each user. The scheduler is responsible for

Table 5 Robot interaction modalities for user profiles

User profile	Interaction modality
Openness [High], Neuroticism [Low]	Distance [Near]
Openness [High], Neuroticism [High]	Distance [Medium]
Openness [Low], Neuroticism [Low]	Distance [Medium]
Openness [Low], Neuroticism [High]	Distance [Far]
Impairment [Visual]	Interaction_Mode [GUI-Voice]
Impairment [Visual]	Led_Lights [On]
Impairment [Visual]	Sound [Regular]
Impairment [Hearing]	Interaction_Mode [GUI]
Impairment [Hearing]	Sound [High]
Impairment [Hearing]	Led_Lights [On]
Impairment [None]	Sound [Regular]
Impairment [None]	Led_Lights [Off]
Impairment [None]	Interaction_Mode [GUI]

scheduling the sequence of assistive tasks by assigning the corresponding abstract workflow a *validity time*. It is set according to the time range the corresponding activity is planned to take place in the daily routine. In fact, monitoring activities, reminding medicines, and suggesting entertainments cannot be delivered outside the time interval planned in the daily routine. The length of the time interval is set also according to the priority and the constraints of the corresponding activity. For example, the time interval for the reminding medicine task is shorter since the patients cannot take the medicine at the wrong time, while for entertainment activities the time interval is longer to allow for different contents such as videos, music, and so on, to be played by the user. The scheduler assigns to each abstract workflow also a frequency value at which the corresponding task can be repeated, set according to the Cognitive and Psychological user profile, in the case of either a failure of some component service or of an unsuccessful output due to the lack of user response. The number of allowed repetitions is guaranteed to occur always within the validity time of the corresponding task. In addition, the scheduler processes data in the Daily Observations to detect if dynamic changes occurred that require changes in the planned assistive tasks scheduled for execution.

The QoS Manager is responsible for selecting a daily assistive action for each abstract service of the abstract workflows and for setting their corresponding QoS parameter values regarding the interaction modalities. It processes the User Preferences, and the Cognitive and Psychological profile, to select the corresponding executable assistive tasks.

The Cron Manager is responsible for the actual execution of the daily assistive plan by triggering it using a time-based event-driven policy. It consists in activating the execution of the component executable assistive tasks obtained from the QoS manager. The Cron Manager invokes the daily assistive actions by communicating with the application server they are registered in. It is responsible for managing the correct execution of the temporal sequence of the planned assistive tasks, preventing their overlapping or conflicting execution, so guaranteeing their timely execution and adherence to both their schedule and their validity time.

4.6 Dynamic adaptation

In addition to user-centric personalization, the adopted service-oriented approach allows also for a dynamic adaptation of the daily assistive plan at the execution time in case of changing conditions that may occur both in the availability of the technological devices used to deliver daily assistive actions and in the user profile data, i.e., the patient status.

Because of the limited use of environmental sensors placed in the patients' houses this dynamic information is registered by updating the Daily Observations of the user's profiling database as the result of the execution of some daily assistive actions, as a *Check* action reporting a bad health state, or by caregivers through a special *Alert* service, as any dynamic change in the daily routine. Some dynamic changes are characterized by a validity time specifying the time the modification is in place for. For example, in the case the user is not available for a time range during the day because of a not planned event, the insertion of this information allows the scheduler module to change the timing of the corresponding assistive tasks, or to disable the execution of the assistive tasks that cannot take place any more.

Let us consider the abstract workflow for the *Entertainment Stimulation* in Fig. 4. It is processed by the Scheduler and the QoS Manager so resulting in the Daily Assistive Plan reported in Fig. 5 (top) ready to be executed by the Cron Manager. During execution, runtime conditions are checked either by processing information in the Daily Observations or as the output of the invoked monitoring services, as the *Check State*. As shown in Fig. 5 (bottom), in the case the user is not present at the scheduled time for the entertainment, the activity is repeated at a later time (if still in its validity time). For what concerns technological adaptation, in case a device is out of power, as for the wearable device as shown in the same figure, or not reachable for problems in the network connections, or not in the availability of the user (e.g., the user could not wear a smartwatch), the Cron Manager implements a recovery mechanism replacing the not available daily assistive action with an equivalent one from a functional point of view but delivered by the robot. The QoS Manager sets the QoS parameter values corresponding to the new selected daily assistive action accordingly. In addition, information regarding the user's mood is used by the QoS manager to change the contents of the suggested entertainment activity, from a video to audio, and the approaching distance of the robot to limit possible discomfort.

Hence, both functional and non-functional adaptation of the robotic application is guaranteed since the binding of abstract services to actual daily assistive actions occurs at the time when the daily assistive plan is scheduled for the execution and the corresponding assistive tasks are triggered, so allowing processing dynamic information if it occurred.

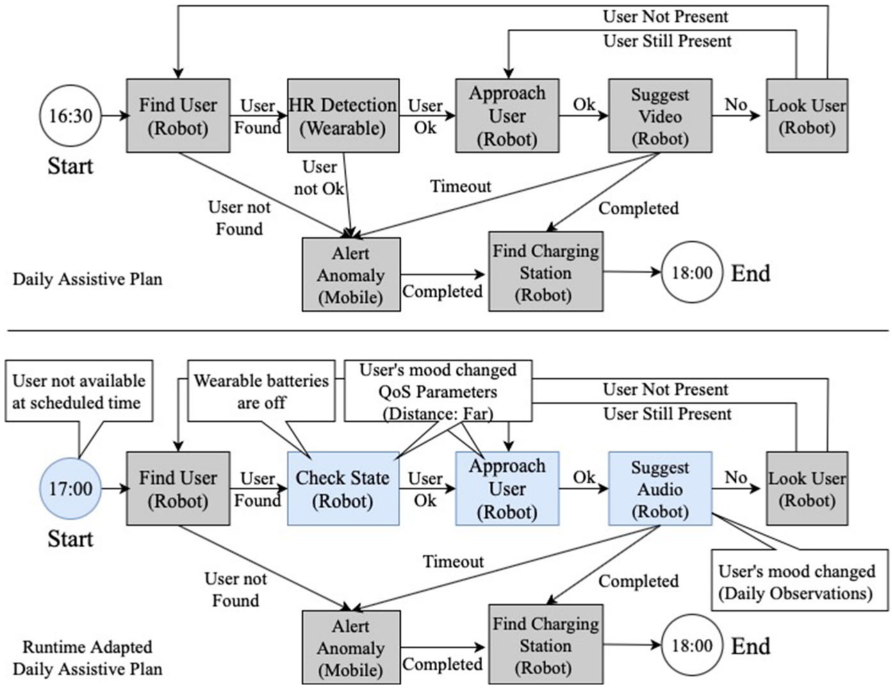


Fig. 5 A daily assistive plan for the *Entertainment Stimulation* task (top) and an example of runtime dynamic adaptation (bottom)

5 Experimental design

All experimental procedures performed with human participants were in accordance with the ethical standards of the institutional and national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. The experimentation was approved (no. 167/18) by the ethical committee of the University of Naples Federico II.

A multiple single-subject study was planned with two objectives: (1) to test the feasibility and reliability of a low-cost robotic system autonomously running in real environments without on-site technical support, and (2) to get information on the patients' acceptability of the proposed robotic assistive system in their home environments. Indeed, individual differences between subjects in terms of cognitive impairments, but also education level, and psychological traits are relevant to the phenomenon of interest, so preventing to conduct statistical analysis that considers different individual factors in the evaluation. In any case, recruiting a large significant number of subjects is difficult due to possible reluctance to be involved in such experimentation and to have an interaction with the robot that lasts for multiple days.

Table 6 Overview of the participants

ID	Gender	Age	Education	Memory Impairments	Familiarity with Tech. [1–5]
1	F	84	13	AD	1
2	M	61	5	MCI	1
3	F	55	8	SMD	3
4	M	68	8	MCI	4.3
5	F	83	18	SMD	2
6	M	78	8	MCI	1
7	M	77	13	MCI	3.7

5.1 Participants

The project experimentation was presented to 40 patients of the Cognitive Disorders and Dementia Center of the Neurology Operating Unit and Epilepsy Center of the Federico II University Hospital (CDCD-Neurology). The diagnosis of mild neurocognitive disorder was performed according to the criteria of the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5): Evidence of modest decline in one or more cognitive domains; Capacity for independence in daily activities is maintained; Cognitive deficits do not occur exclusively in the context of a delirium; Cognitive deficits not better explained by another mental disorder.

For the recruitment of patients, an assessment of their houses was necessary to verify their compliance with specific non-technological requirements mainly for robot navigation. In detail, houses with stairs, high pile carpets, glass doors, and pets were excluded. Moreover, houses with limited space for robot movements were excluded. Specific technological requirements were not considered since the necessary hardware/devices were directly provided to users.

The selected patients were clinically assessed with the Clinical Dementia Rating Scale (CDR) (Morris 1993). They were diagnosed with subjective memory disorder (SMD, corresponding to a CDR value of 0), mild cognitive impairment (MCI, corresponding to a CDR value from 0.5 to 1), or Alzheimer's disease (AD, corresponding to a CDR value of 2).

We obtained a positive response to be enrolled in the experimentation in 14 cases out of 40. Other patients were excluded or refused the trial: 10 patients had pets in the house, 20 did not have valid family support necessary for the presence of the robot, 5 for the presence of stairs in the house or unsuitable space for the robot movements, 1 was illiterate to allow interaction with the robot. Hence, 10 patients were enrolled in the study, including 2 AD patients, 4 MCI patients, and 4 SMD patients. The actual study was possible with 7 patients because an AD worsened considerably, one SMD changed his mind due to changes in the family situation, and one SMD was unable to host the robot because additional carpets were put in the house preventing the robot to move. Data of the 7 patients are reported in Table 6.

All recruited subjects signed the informed consent in the presence of a parent or caregiver. Moreover, they signed the consent to host the robot for the set period and agreed to have the robot at their home for at least two consecutive weeks.

5.2 The smart home environment

The smart environment represents the adopted set of technological devices to be deployed in the patient's home to run the assistive robotic application.

The robot used for the experimentation is the Sanbot Elf (see Fig. 6) developed by Qihan Technology. It is equipped with infrared sensors, omnidirectional locomotion, two cameras (an RGB-D and a full-HD) and touch sensors, a microphone, speakers, a subwoofer, and a full-HD touchscreen. The robot has a moving head with a display that can show different animations of the eyes resembling different emotional expressions. Such expressions are used to differentiate the behaviors (microservices) of the robot when executing a complex task. Moreover, both the head and the fins have light colors that can be changed.

The applications server and the middleware layer run on an Intel NUC7i7-BNH with Intel i7-7567U-3.50 GHz, 16GB DDR4 RAM, and 256 GB SSD communicating with the other devices, including the robot, using a Wi-Fi router. The robot and the Intel NUC represent the core of the assistive application and are sufficient to execute all the planned activities.

The other provided devices are a Polar Android M-600 smartwatch that mounts an accelerometer, gyroscope, optical heart rate measurement with six LEDs that can be worn by the patient; two iBeacons, capable of transmitting a signal using Bluetooth

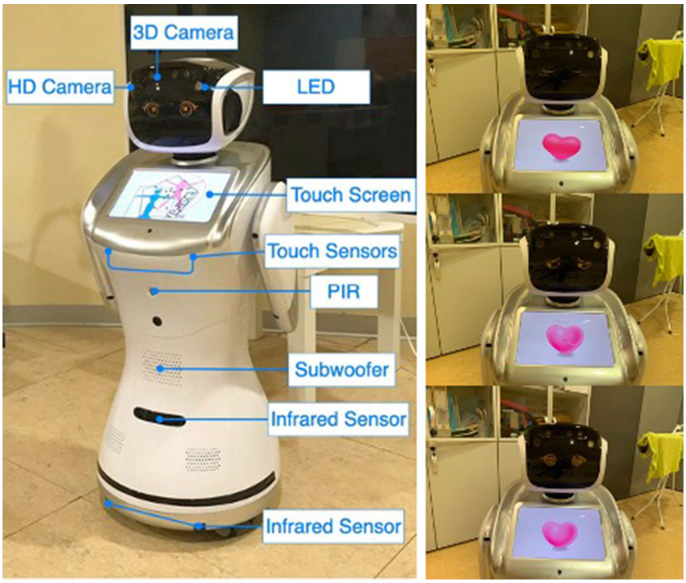


Fig. 6 Sanbot Elf robot and its hardware components

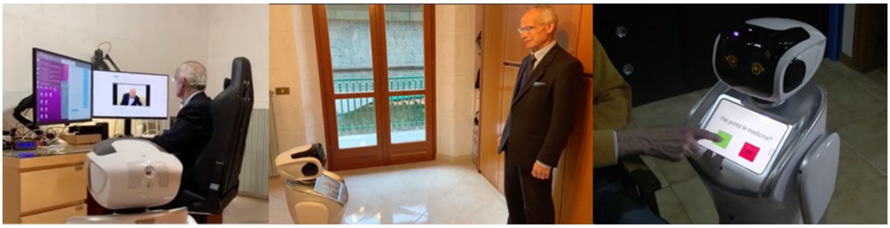


Fig. 7 Monitoring and reminder activities in a real setting

Low Energy (BLE) technology (the strength of the RSSI—Receive Signal Strength Indicator—was used to define proximity relations) that were used for room labeling (e.g., the kitchen and the living room); an Android smartphone that can be used by a caregiver to receive notifications from the robotic system for dangerous situations or requests for intervention.

5.3 Experimental procedure

The experimentation, conducted in Italy, started in June 2019 and ended in January 2020. The robot was left in the participant's house 24 hours per day and for at least 14 days (see Fig. 7). The patient and a family member were instructed on how to switch the robot off and on and given a general description of the robot's functionalities and the provided assistive services. A researcher spent one or two hours with each patient showing how the robot would work and when, how to interact with it using the touchscreen, and answering all the questions asked by the patient. The researcher's contact details were left to the patient for being contacted in the case of any doubt.

The following assistive tasks were considered in the experimentation:

1. WakeUp Monitor
2. Entertainment Stimulation
3. Lunch Monitor
4. Remind Medicine
5. Dinner Monitor

The service Check Health State is invoked at the beginning of each assistive task to verify that the health state of the user does not prevent its execution.

Several sets of data have been collected: cognitive and personality tests, interviews, daily questionnaires, and data automatically collected in log files during the experimentation at home. It should be underlined, that for privacy reasons due to the experimentation in not controlled environments such as private homes, no video recording, as well as skeleton tracking, was included as means to collect additional information. Since the proposed robotic application is centered on the patient's needs and personal characteristics, no data were collected regarding the perception or the subjective evaluation of caregivers or family members.

Table 7 Number of executed workflows for each patient

Number of days Patient	14 P 1	11 P 2	11 P 3	17 P 4	25 P 5	25 P 6	15 P 7
WakeUp monitoring	17	10	7	11	8	0	0
Lunch monitoring	9	11	16	18	14	0	9
Dinner monitoring	6	0	12	6	11	0	9
Remind medicines	4	16	18	18	23	103	2
Entertain. Stimulation	25	10	12	27	30	107	29
Total	61	37	58	69	78	210	49

6 Experimental results

The results gathered during the field experimentation to test the system reliability concern data of the actual execution of the daily assistive plans for the whole experimental phase. The ones regarding the system acceptability rely on questionnaires and interviews submitted to the enrolled patients.

6.1 Results of the execution of the personalized daily assistive plan

The data concerning the execution of the daily assistive plan were collected in log files to verify its adherence to the patient daily routine. Each daily assistive plan is composed of a maximum of 8 assistive tasks delivered in a day. Since 5 different types of assistive tasks were considered, some of them are executed more than once according to the patient's needs, such as reminding medicine or suggesting entertainment tasks. Each day, the last activity of the robot is the execution of the *FindChargingStation* service to automatically find the charging station to recharge its battery during the night. The different sets of data are analyzed to assess the daily operativity of the robotic application and the correct functioning of the middleware responsible for its management.

In Table 7, the types and the number of assistive tasks composing the daily assistive plan together with the days of the experimentation for each patient are reported. The columns reporting a 0 value refer to tasks not executed, while a value exceeding the number of days for the experimentation means that the task is executed more than once during the day. There are different reasons why an assistive task is not executed:

- The task was not included in the daily routine because not required by the patient or her/his relatives since it was considered not necessary;
- The task corresponds to an activity that takes place in a room not available for the robot to enter for infrastructural reasons (e.g., the presence of delicate furniture);
- Other tasks such as the *RemindMedicine* had to be executed more times during the day following the pharmacological therapy of the patient, so other tasks with less priority were dismissed to meet the requirement to execute a maximum of 8 assistive tasks per day;

Table 8 Average duration for each workflow type and each patient

Workflow	P1	P2	P3	P4	P5	P6	P7
WakeUp Mon.	0:32:52	0:47:10	0:37:08	0:48:23	0:28:44	0:00:00	0:00:00
Lunch Mon.	0:40:22	1:05:21	0:49:15	0:34:13	0:25:14	0:00:00	0:42:36
Dinner Mon.	0:37:10	0:00:00	0:56:03	0:52:05	0:22:06	0:00:00	0:34:03
Remind Med.	0:31:23	0:59:28	0:41:59	0:56:50	0:27:16	0:42:13	0:48:35
Entertain. Stim.	1:05:03	1:38:48	1:05:47	1:17:37	0:52:55	0:58:47	1:01:22

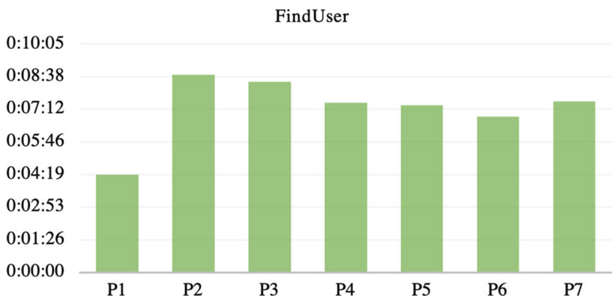


Fig. 8 Average execution time for the *find user* service

- Only one assistive task can be executed in a time interval, so if at lunchtime the patient was to be reminded to take medicine, the task to monitor lunch was dismissed.

In Table 8, the average duration of each type of assistive task for each patient mediated on the number of days of the experimentation is reported. Results show that even though the assistive tasks are composed of the same number of microservices, their execution time differs because of the different execution times of the *FindUser* microservice, as reported in Fig. 8. This is mainly due to the different environments where the robot is located requiring different times to locate the user and the different number of relatives living in the house that could be detected by the robot delaying the time necessary to identify the patient.

The average duration of each workflow for each patient and the number of executed workflows confirmed the adherence of the scheduled assistive tasks to the timing of the daily routines of patients (see Table 8). The adoption of the validity time for each task, when they are scheduled for execution, allowed to avoid time overlapping, and hence failures, of the planned tasks. So, the validity time is crucial and whenever the execution of an assistive task does not meet it, the Alert service is invoked.

The *Entertainment Stimulation* task reports the most variable execution times as reported in Fig. 9. This is due to the different times required to play different types of entertainment like videos, music, games, and documentaries. The data collected on the played entertainments are also analyzed as feedback when users accepted and played them, to check whether the preferences they expressed during the interviews were valid during the experimentation, or if they were stimulated by the presence of the robot to experience different entertainments.

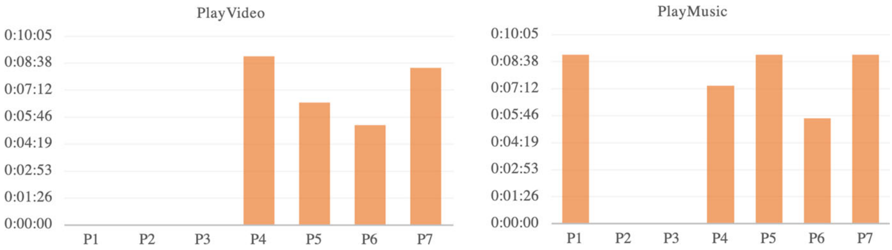


Fig. 9 Average execution time for the *play video* and *play music* service

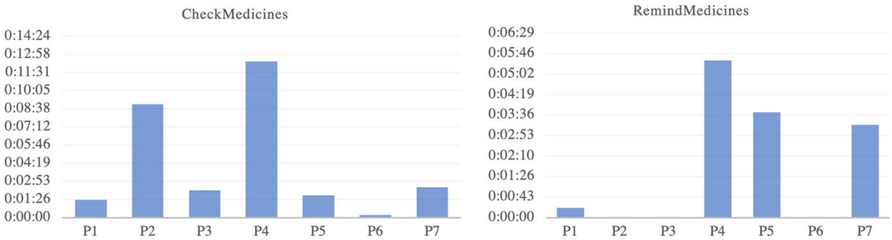


Fig. 10 Average execution time for the *CheckMedicine* and *RemindMedicine* task

One of the most important assistive tasks to be executed with strict adherence to the daily routine is *RemindMedicine*. The task consists of reminding the patient to take a medication in the case the patient forgot to do it, i.e., if *CheckMedicine* reports a "no" output. In such a case the assistive task is repeated until either the *CheckMedicine* reports a "yes" output, or the validity time expires requiring an alert to be sent to the caregiver for immediate action. For this reason, as reported in Fig. 10, the *CheckMedicine* and the *RemindMedicine* microservices are executed a different number of times for each user depending on their responses. The patients P2 and P3 and P6 did not require a reminder, while P1, P4, P5, and P7 were to be reminded several times before actually taking medicines. These differences are due to the different cognitive statuses of the patients (the worse the memory impairment is, the higher the number of reminders is), and the presence of caregivers or relatives that support them when crucial tasks have to be undertaken.

6.2 Results on acceptance of the personalized daily assistive plan

During the experimentation, subjective information on how the interaction with the robot was perceived was gathered through a very simple questionnaire. The patient was asked to fill it every day by selecting one of the three emoticons representing the satisfaction degree with the following metrics: Sad = 1, Neutral = 2, Happy = 3. Results showed that out of 7 patients, 5 patients reported an average evaluation above 2 (neutral), while patients P4 and P7 were below 2 (see Table 9). In particular, P4 and P7 were the patients with a greater familiarity with technologies, and so with the higher expectations about the robot's behavior. To evaluate a possible correlation between the familiarity with technology of the patients and the subjective satisfaction evaluation of

Table 9 Average value of the daily subjective evaluation for each patient

Patient ID	P1	P2	P3	P4	P5	P6	P7
Average evaluation	2.8	2.3	2.1	1.5	2.8	2.7	1

Table 10 Cronbach's alpha values after removing items

Construct	α	Construct	α
ANX	1.0	PEOU	0.745
ATT	0.879	PS	0.816
FC	–	PU	0.889
ITU	0.977	SI	0.816
PAD	0.612	SP	0.876
PENJ	0.884	TRUST	0.998

the use of the robot, we calculate the Pearson correlation. A strong significant negative correlation between the two variables was found with $\rho = -0.84$ and $p = .018$. There is no significant Pearson correlation between subjective satisfaction and years of education or age.

Moreover, to evaluate the user acceptance of the developed system, the UTAUT questionnaire was used (Heerink et al. 2010). The questionnaire has been translated into Italian. The translation was examined at a consensus meeting, back-translated, and approved at a second consensus meeting. A comprehension test was carried out on a subgroup of 15 individuals.

The UTAUT questionnaire aims at evaluating the user intentions to use new technology and it consists of 41 items and explores 12 constructs: Anxiety (ANX), Attitude (ATT), Facilitating Conditions (FC), Intention to Use (ITU), Perceived Adaptability (PAD), Perceived Enjoyment (PENJ), Perceived Ease of Use (PEOU), Perceived Sociability (PS), Perceived Usefulness (PU), Social Influence (SI), Social Presence (SP) and Trust (TR). The Likert scale to score the items ranges from 1 to 5. The SPSS software version 26 was used to analyze the data and calculate the statistics.

First of all, we calculated the Cronbach alpha (CA) coefficient to estimate the internal consistency of each construct. For ATT, ITU, PENJ, PU, SI, and TR, we had an α considering all the items above 0.8 that indicated a high level of internal consistency. For ANX, PAD, PEOU, PS, and SP some items have been removed to reach sufficient reliability. FC construct was removed because not reliable.

The descriptive statistics (mean, minimum, maximum, standard deviation) for the 12 constructs are reported in Table 11. For each construct, the result has been divided with respect to the number of items for the construct. A positive perception of a participant is assumed when the construct score is greater than 2.5, while a negative perception is when the average score is lower than 2.5. On average, the participants had a good acceptance of the robotic application showing good results in terms of having low anxiety in using the robot (for ANX a high value indicates low anxiety), good feelings toward it (ATT), and a well-perceived enjoyment (PENJ). The robot was perceived as adaptable (PAD) and useful (PU). In addition, the system was evaluated with a satisfactory Perceived Easy Of Use (PEOU) value. According to (Casey et al.

Table 11 UTAUT results after the interaction with the robot

Construct		Avg	Std	Min	Max
ANX	Anxiety	4.43	1.51	1.00	5.00
ATT	Attitude	4.19	0.96	2.33	5.00
FC	Facilitating conditions	3.43	0.79	2.50	4.50
ITU	Intention to use	2.14	1.14	1.00	3.67
PAD	Perceived adaptability	3.00	0.96	2.00	4.50
PENJ	Perceived enjoyment	4.09	1.09	1.80	5.00
PEOU	Perceived ease of use	2.64	1.14	1.00	4.00
PS	Perceived sociability	3.00	1.20	1.00	4.33
PU	Perceived usefulness	3.67	1.58	1.00	5.00
SI	Social influence	4.14	1.11	2.00	5.00
SP	Social presence	2.39	1.39	1.00	5.00
TR	Trust	3.64	1.49	1.00	5.00

2016; Koh et al. 2021), this is evidence of the possible acceptance and usability of a system with PwD due to their cognitive deficit. Moreover, the Perceived Utility (PU) is another important factor to consider since a mismatch between the patients' needs and the offered technological solutions constitutes a barrier to acceptance and adoption (Casey et al. 2016).

The only constructs we found below average are intention to use (ITU) and social presence (SP). We believe that for intention to use the actual items of the construct were not correctly interpreted by the patients and the item constructs were not suitable to evaluate ITU in our experimentation. One of the statements to evaluate ITU was: "I'm certain to use the robot during the next few days." But the UTAUT questionnaire was performed on the last day of the experimentation with the patients aware that the experimentation was over and they were not going to use the robot again. So, their answers were conditioned by this information and they could not reflect the real intention to use the system again. Hence, the form of such a question should be revised to be properly used. Moreover, while the robot was perceived as showing sociable behaviors (PS), it was moderately perceived as a social entity.

The Shapiro–Wilk test on construct values showed that the data are normally distributed. Hence, to better understand relationships between constructs, we calculated Pearson's correlations for parametric values. Once significant correlations were found between variables, the regression analysis was used to confirm the predictive role of one factor (predictor variable) to another (dependent variable). Two-tailed correlation results are reported in Table 12.

In detail, the perceived sociability (PS) of the robot was found to be a good predictor of the perceived usefulness (PU) with an $R^2 = 0.828$, $\beta = .91$, $t = 4.907$, and $\rho < 0.05$, meaning that the perception of the ability of the robot to express a social behavior has an impact on its perceived utility. Moreover, social influence (SI) was found to be a good predictor of attitude toward technology (ATT) with $R^2 = .980$, $\beta = .99$, $t = 15.532$, and $\rho < 0.001$ possibly meaning that when having a low familiarity with

Table 12 Significant Pearson correlations between UTAUT constructs

	ANX	ATT	PENJ	PS	PU	SI	TR
ANX							.781*
ATT			.851*	.787*		.990**	
PENJ		.851*		.890**	.938**	.869*	
PS		.787*	.890**		.910**	.814*	
PU			.938**	.910**			
SI		.990**	.869*	.814*			
TR	.781*						

* is for $p < 0.05$ and ** is for $p < 0.001$

technology, as for the majority of the considered subjects, there is a strong correlation between possible influence of relatives and caregivers on the willingness/attitude to use the robot. Finally, both PU and ATT resulted in being good predictors for the perceived enjoyment (PENJ) with $R^2 = .875$, for PU with $\beta = .585$, $t = 2.409$, and for ATT with $\beta = .432$, $t = 1.782$.

6.3 Patients interviews

Here, qualitative data from interviews with the patients are reported. Indeed, a crucial source of information was gathered through interactions between the researchers responsible for the experimentation and the patients both via informative telephone calls and visits at home taking place during the experimentation, and a friendly exchange of opinions at the end of the experimentation period. It was difficult to formalize the obtained information, but since this feedback was very important to understand patients' perceptions during the experimentation, we report here the main collected results.

The robot was never turned off by the users, as also verified in the log files. Even though the robot was not scheduled to move during the night to recharge its batteries, one patient (P2) reported that he locked the door of the room where the robot was located for the first two nights, until he was sure it was not moving during the night.

Only 2 patients, P4 and P7, reported negative feedback about the experience with the robot complaining about the lack of vocal interaction. In addition, they expected the robot could be instructed to perform tasks required by them through its display monitor, or it could move when they wanted. One of the patients declared to have skills in using the computer and hence to be able to program it. He/She was expecting to be able to interact with it as with a vocal assistant like Alexa. Moreover, the homes of these patients were quite small and not very suitable to allow the robot to move easily, so they were disappointed by the few interactions due to the failures of some assistive tasks.

The other 5 patients were all very enthusiastic about the experience with the robot, and they all asked for it to stay for more time. At the end of the experimentation, they declared that the robot became like a friend making their time at home more pleasant and making them feel more occupied than usual. They were very thrilled by the fact that the robot recognized and interacted only with them, so making them feel important to the robot. Above all, they appreciated the help they received in being reminded of their medication therapy, and the possibility to have the entertainments they preferred (music tracks they liked that reminded them of their past times, recipes videos for those who like cooking, sports videos for who likes sport, and so on).

The patient with the worse cognitive impairment (CDR = 2) was very reluctant at the beginning almost refusing to have the robot at the first sight. But when the robot started interacting every day, the attitude of the patient changed completely, and the robot was perceived as a family person.

The patients that had the robot for longer times (P5 and P6) were the most enthusiastic about it. This is an encouraging result since, even though supported by few data for deriving conclusions, it may suggest that the more used the patient becomes to the robot's presence, the higher its acceptance could be. One patient wrote an appreciation letter to the researchers thanking them for the special experience at the end of the experimentation. The other one developed a so close relationship with the robot expressing even worries when the robot stopped working for a day because it was out of charge (it was not recharged in time) and it did not move as in the previous days. The patient perceived the robot as a real person not feeling well. This collected information about the feelings of patients for the robot presence is in line with the UTAUT results that reported for these two patients an high value for the social presence construct, which is also higher compared to the other patients.

7 Discussion

Testing assistive robotics applications in real settings and without the supervision of technicians remains a significant challenge despite the available technologies.

The adoption of a service-oriented approach allowed us to decouple the functioning of the developed microservices from both the design and implementation of the complete robotic application and the collection of user data. In such a way, it was possible to perform in parallel the testing of the system in the controlled environment of the University robotic laboratory, during the development phase of the project, while completing the implementation of all necessary functionalities. This was a fundamental step to improve the reliability of the robotic application to be then deployed in home environments.

In addition, the service-oriented approach proved to be a promising way in the direction of developing plug-and-play assistive applications crucial for personalizing home care in domains characterized by high rate progress in technological and service development. In fact, with the service-oriented approach, platform dependence concerns only the actual implementation of assistive actions. The implementation is transparent to the system once they are registered in an application server according to agreed interfaces for their invocation and interoperability.

Nevertheless, to have significant results from the interaction, it is necessary to obtain a significant maturity and dependability of the developed services (Koh et al. 2021). This is even more crucial when dealing with robot navigation and interaction capabilities for home monitoring. Indeed, most efforts were devoted to guaranteeing the functioning of the system in a not controlled and supervised environment without relying on any remote control.

User localization is one of the more time-consuming services in real home environments when not supported by additional devices. The use of a low-cost social robot for the experimentation allowed us to use a robot that could be safely deployed in a home environment, but with a limited set of sensors for navigation. In our experimentation, the robot was able to locate the user (if present) in seven minutes on average. As the results showed, the time for accomplishing the scheduled workflows heavily depends on the house configuration and the number of persons in the environment. With more reliable sensors the robot could be able to improve performance by deploying localization and mapping mechanisms and by learning user-preferred locations for their routines. However, in our domain the time spent by the robot in finding the user was acceptable and so the benefit of having a low-cost robot overcomes the possible cost of time spent in localizing the user. Moreover, in future development, the presence of beacons in the house could be exploited to speed up the robot navigation by implementing algorithms that direct the user searching process toward known areas.

As highlighted in (Koh et al. 2021), the match between social robots' functions and users' needs is evaluated as an enabler for the adoption of assistive social robot technologies. However, when considering patients' clinical needs (as reminders or monitoring), these have to be balanced with additional functionalities that match also with a subjective perception of enjoyment. In many cases, the users enjoyed the entertainment activities provided by the robot. Indeed, the system was evaluated with a high value of perceived usefulness (avg PU = 3.67) with the perceived sociability of the robot being a good predictor for PU. The role of family members and caregivers in supporting the acceptance of the technology by the patients is fundamental considering that, in our results, social influence (SI) is a good predictor of attitude toward technology (ATT), and both ATT and PU are predictors of Perceived Enjoyment (scoring in the average PENJ = 4.09). Results are also in line with a very high average value of the Anxiety item (average ANX = 4.43), meaning that there was no anxiety in using the robot after the experimentation.

Also, we found that in the case of initial reluctance or skepticism (as showed by patient P1), a positive perception was obtained at the end of the experimentation. A positive perception was also found in patients experiencing longer interaction with the robot. In this sense, daily verbal comments and observations provided additional insights during the experimentation with respect to simple ratings of the acceptance.

7.1 Limitations and future perspective

In the current release of the system for the experimentation, the abstract workflows representing the considered assistive tasks are predefined with the help of doctors and psychologists to be fully compliant with the patient needs and manually designed in sub-components by developers. They are included in configuration files to be processed by the middleware. Additional assistive tasks can be added by including them in the configuration files. Nevertheless, a different module not yet integrated into the systems is responsible for the automatic generation of abstract workflows (Di Napoli et al. 2018).

The adoption of long-term robotic applications requires continuous updates of the user profile due to the rapid evolution of their cognitive impairment and consequently their personality profile (D'Iorio et al. 2018). We relied on updates either manually inserted by caregivers, or as a result of specific services ad hoc invoked. Moreover, gathering correct information from patients for entertaining preferences may be difficult. So, the possibility of deploying recommender systems for learning entertainment preferences is desirable.

The technological constraints impacting the experimentation were not only due to cost and infrastructure limitations but also to privacy and security reasons. No network connection from the house to the outside was allowed, as well as no personal information from the camera was allowed to be stored. These ethical issues pose challenges for the evaluation of results regarding the perception of the received assistance from the user, and the possibility of correctly evaluating the performance of some developed services in the wild. For example, while activity recognition was tested on laboratory data (Ercolano and Rossi 2021), no video recording, as well as skeleton tracking, was included as means of validation during the experimentation. How to properly evaluate these functionalities in an ecologically relevant environment is an open issue. The same holds for the *checkMedicine* service, which is a very delicate aspect of an assistive plan requiring sophisticated continuous monitoring to detect if the patient really takes the medicine. We relied on a question asked by the robot to the user and to a family member to check that the reply was reliable.

As emerged from the opinions collected from the patients' interviews, the time the robot is left at home may play a crucial role in the perception of its usefulness, and in the change that may occur in the perception over time. Of course, a study on this aspect was not undertaken since the times for the experimentation for each patient were constrained by the project timing and patient availability. All collected data and their analysis suffer, as pointed out, from the difficulty of finding patients with the right conditions to be enrolled.

In addition, the negative relationship between the user's familiarity with technology and the satisfaction with the system needs to be further explored since there could be different reasons for different users. For example, if they use technology frequently they could expect a higher level of interface performance that the system did not deliver, or they could feel their needs are already fulfilled by other devices and services already in use in their everyday life.

Moreover, the results on the patient's acceptability of the robot were influenced by the lack of the natural language understanding not included in the robot's functionality. It requires the availability of an internet connection that, beyond security reasons, was also not available at all for the recruited patients. So it would imply an additional technological infrastructure and cost due to also the necessity of directional, noise-canceling, microphones and the subscription to NLP cloud services. For future works, we are working on feasible, cost-effective, approaches to handle natural language processing (NLP) and dialogue. However, it has to be noted that the use of NLP in the development of HRI application in the wild is particularly challenging, especially in the case of interaction with elderly persons that may have a problem with fluency or may use dialects.

Finally, since the proposed robotic application was intended to be centered on the patient's needs and personal characteristics, no data were collected regarding the perception or the subjective evaluation of caregivers or family members. Caregivers' evaluations of robotic assistive care, as assessed in Ghafurian et al. (2021), would have provided useful additional info.

8 Conclusions

Several projects have been funded for developing assistive robotics applications for elderly care with a general good acceptance of the assistive technology (Broadbent et al. 2016). However, many of them are still experimented within controlled environments such as research laboratories, or retirement homes. There is an increasing need of testing these technologies in the field to improve findings of people's reactions when using social robots in their private homes (Jung and Hinds 2018). Experimenting with robotic applications in unsupervised environments requires addressing different technical and ethical problems, so imposing trade-offs in the experimental evaluations.

The UPA4SAR project addressed these challenges by designing and developing a robotic application for home care of the elderly affected by cognitive impairments to be deployed and experimented with in home environments with patients. To provide a robotic assistive application that can be personalized and adapted to each specific user, it was designed and implemented according to a service-oriented approach in terms of compositions of services. The concept of service is used to separately represent the entities that may be personalized. They concern the resources/devices, which can be different for each home patient, the functionalities they provide, which can be different according to the patient's assistive needs, and the provision modalities the functionalities are delivered with that are different according to the user' profile.

In addition, the choice to design a daily assistive plan as a composition of assistive tasks, that are in turn a composition of services, allows for addressing different levels of personalization and keeping them clearly separated. So each one can be managed when necessary and when possible. A monolithic representation of an assistive plan or even an assistive task would prevent the modular approach for personalization. For example, personalization of interaction modalities concerns only specific services, as well as the selection of a specific device providing it. Instead, personalization of the repetition frequency or the timing concern the assistive task as a whole, while personalization of the types and number of assistive tasks concerns the daily assistive plan. The proposed modular approach allows assistive applications to be deployed for every single user and different technological environments.

Personalization and adaptation of the robotic applications take into account the available technology, the home environment structure, and more importantly the patient's personality traits, her/his cognitive state, and her/his needs and preferences. According to the information collected about the daily routines of patients, it is possible to individuate the type of assistive tasks they need. The tasks are then personalized at the execution time according to the specific user profile and adapted to the current situation. The robot can carry out these activities with full autonomy. The scheduling and the actual execution of such activities are performed by the middleware layer managing the functional and non-functional characteristics of the assistive application, together with recovery mechanisms from possible failures.

The on-field experimentation was conducted with 7 patients at their homes for a total time of 118 days. The patients' enrolling and profiling were carried out during the application design and development of the system. The reported results showed that personalization and adaptation for both functional and non-functional characteristics of an assistive application play a fundamental role in the acceptance of new and unfamiliar technologies for a fragile class of users such as the elderly affected by cognitive impairments.

The data collected from different sources allowed to derive several challenges and opportunities to be considered when developing these types of applications. However, in general, a positive outcome when using a robotic application in a not controlled domestic environment resulted both in the system reliability and robustness, and the system acceptability from users, unexpectedly even in the case of a low education level. In addition, a promising result is that patients who experienced the robot for a long time were the ones more satisfied with the robot's presence. Of course, this result needs to be supported by further experimentation with more patients and for a longer time.

Funding Open access funding provided by Università degli Studi di Napoli Federico II within the CRUI-CARE Agreement.

References

Ahmad, M., Mubin, O., Orlando, J.: A systematic review of adaptivity in human-robot interaction. Multimodal Technol. Interact. **1**(3) (2017)

Andriella, A., Torras, C., Alenyà, G.: Short-term human-robot interaction adaptability in real-world environments. Int. J. Soc. Robot. **12**(3), 639–657 (2020)

Biancardi, B., Dermouche, S., Pelachaud, C.: Adaptation mechanisms in human-agent interaction: effects on user's impressions and engagement. Front. Comput. Sci. **3**, 69 (2021)

Bonaccorsi, M., Fiorini, L., Cavallo, F., Saffiotti, A., Dario, P.: A cloud robotics solution to improve social assistive robots for active and healthy aging. Int. J. Soc. Robot. **8**(3), 393–408 (2016)

Broadbent, E., Kerse, N., Peri, K., Robinson, H., Jayawardena, C., Kuo, T., Datta, C., Stafford, R., Butler, H., Jawalkar, P., Amor, M., Robins, B., MacDonald, B.: Benefits and problems of health-care robots in aged care settings: A comparison trial. Australas. J. Ageing **35**(1), 23–29 (2016)

Cakmak, M., Srinivasa, S., Lee, M., Forlizzi, J., Kiesler, S.: Human preferences for robot-human hand-over configurations. In: IEEE international conference on intelligent robots and systems, pp. 1986–1993 (2011)

Casey, D., Felzmann, H., Pegman, G., Kouroupetroglou, C., Murphy, K., Koumpis, A., Whelan, S.: What people with dementia want: Designing mario an acceptable robot companion. In: Computers helping people with special needs, Springer International Publishing, Cham, pp. 318–325 (2016)

Castellano, G., Aylett, R., Dautenhahn, K., Paiva, A., McOwan, P., Ho, S.: Long-term affect sensitive and socially interactive companions. In: Proceedings of fourth international workshop on human-computer conversation, (2008)

Cavallo, F., Esposito, R., Limosani, R., Manzi, A., Bevilacqua, R., Felici, E., Di Nuovo, A., Cangelosi, A., Lattanzio, F., Dario, P.: Robotic services acceptance in smart environments with older adults: User satisfaction and acceptability study. J. Med. Internet Res. **20**(9), e264–e264 (2018)

Chiaravalloti, N., Goverover, Y.: Changes in the brain: impact on daily life. Springer, New York (2016)

De Benedictis, R., Cesta, A., Coraci, L., Cortellessa, G., Orlandini, A.: Adaptive Reminders in an Ambient Assisted Living Environment, Springer International Publishing, Cham, pp 219–230 (2015)

De Carolis, B., Ferilli, S., Palestra, G.: Simulating empathic behavior in a social assistive robot. Multimed. Tools Appl. **76**(4), 5073–5094 (2017)

Di Napoli, C., Rossi, S.: A layered architecture for socially assistive robotics as a service. In: 2019 IEEE international conference on systems, man and cybernetics (SMC), pp 352–357 (2019)

Di Napoli, C., Sabatucci, L., Cossentino, M., Rossi, S.: Generating and instantiating abstract workflows with qos user requirements. In: Proceedings of 9th international conference on agents and artificial intelligence, Springer, LNCS, pp 156–170 (2017)

Di Napoli, C., Valentino, M., Sabatucci, L., Cossentino, M.: Adaptive workflows of home-care services. In: 2018 IEEE 27th international conference on enabling technologies: infrastructure for collaborative enterprises (WETICE), IEEE, pp 3–8 (2018)

Di Napoli, C., Del Grosso, E., Rossi, S.: Robotic entertainments as personalizable workflow of services: a home-care case study. In: 2019 IEEE 28th international conference on enabling technologies: infrastructure for collaborative enterprises (WETICE), IEEE, pp 15–20 (2019)

D'Iorio, A., Garramone, F., Piscopo, F., Baiano, C., Raimo, S., Santangelo, G.: Meta-analysis of personality traits in alzheimer's disease: a comparison with healthy subjects. J. Alzheimers Dis. **62**, 773–787 (2018)

Do, H.M., Pham, M., Sheng, W., Yang, D., Liu, M.: Rish: a robot-integrated smart home for elderly care. Robot. Auton. Syst. **101**, 74–92 (2018)

Duque, I., Dautenhahn, K., Koay, K.L., l Willcock, Christianson B.: A different approach of using personas in human-robot interaction: Integrating personas as computational models to modify robot companions' behaviour. In: 2013 IEEE RO-MAN, pp 424–429 (2013)

Ercolano, G., Rossi, S.: Combining cnn and lstm for activity of daily living recognition with a 3d matrix skeleton representation. Intel. Serv. Robot. **14**(2), 175–185 (2021)

Ercolano, G., Riccio, D., Rossi, S.: Two deep approaches for adl recognition: a multi-scale lstm and a cnn-lstm with a 3d matrix skeleton representation. In: 2017 26th IEEE international symposium on robot and human interactive communication (RO-MAN), pp 877–882 (2017)

Ercolano, G., Raggioli, L., Leone, E., Ruocco. M., Savino, E., Rossi, S.: Seeking and approaching users in domestic environments: testing a reactive approach on two commercial robots. In: 2018 27th IEEE international symposium on robot and human interactive communication (RO-MAN), pp 808–813 (2018)

Ercolano, G., Lambiase, P.D., Leone, E., Raggioli, L., Trepiccione, D., Rossil, S.: Socially assistive robot's behaviors using microservices. In: 28th IEEE international conference on robot and human interactive communication (RO-MAN), pp 1–6 (2019)

Filippeschi, A., Peppoloni, L., Kostavelis, I., Gerłowska, J., Ruffaldi, E., Giakoumis, D., Tzovaras, D., Rejdak, K., Avizzano, C.A.: Towards skills evaluation of elderly for human-robot interaction. In: 2018 27th IEEE international symposium on robot and human interactive communication (RO-MAN), pp 886–892 (2018)

Fischinger, D., Einramhof, P., Papoutsakis, K., Wohlkinger, W., Mayer, P., Panek, P., Hofmann, S., Koertner, T., Weiss, A., Argyros, A., Vincze, M.: Hobbit, a care robot supporting independent living at home: first prototype and lessons learned. Robot. Auton. Syst. **75**, 60–78 (2016)

Francillette, Y., Boucher, E., Bier, N., Lussier, M., Bouchard, K., Belchior, P., Gaboury, S.: Modeling the behavior of persons with mild cognitive impairment or alzheimer's for intelligent environment simulation. User Model. User-Adap. Inter. **30**(5), 895–947 (2020)

Garcìa-Betances, R.I., Cabrera-Umpiérrez, M.F., Ottaviano, M., Pastorino, M., Arredondo, M.T.: Parametric cognitive modeling of information and computer technology usage by people with aging- and disability-derived functional impairments. Sensors **16**(2), (2016) Ghafurian, M., Hoey, J., Dautenhahn, K.: Social robots for the care of persons with dementia: A systematic review. J. Hum-Robot. Interact. **10**(4), (2021)

Gu, T., Begum, M., Zhang, N., Xu, D., Arthanat, S., LaRoche, D. An adaptive software framework for dementia-care robots. In: 2020 international conference on automated planning and scheduling (ICAPS), (2020)

Heerink, M., Kröse, B., Evers, V., Wielinga, B.: Assessing acceptance of assistive social agent technology by older adults: the almere model. Int. J. Soc. Robot. **2**(4), 361–375 (2010)

Johnson, M.J., Johnson, M.A., Sefcik, J.S., Cacchione, P.Z., Mucchiani, C., Lau, T., Yim, M.: Task and design requirements for an affordable mobile service robot for elder care in an all-inclusive care for elders assisted-living setting. Int. J. Soc. Robot. **12**(5), 989–1008 (2020)

Jung, M., Hinds, P.: Robots in the wild: a time for more robust theories of human-robot interaction. J. Hum-Robot. Interact. **7**(1), (2018)

Karami, A.B., Sehaba, K., Encelle, B. (2013) Amanikandfavzxjnviudaptive and personalised robots - learning from users' feedback. In: 2013 IEEE 25th International Conference on Tools with Artificial Intelligence, pp 626–632

Koh, W.Q., Felding, S.A., Budak, K.B., Toomey, E., Casey, D.: Barriers and facilitators to the implementation of social robots for older adults and people with dementia: a scoping review. BMC Geriatr. **21**(1), 351 (2021)

Kostavelis, I., Vasileiadis, M., Skartados, E., Kargakos, A., Giakoumis, D., Bouganis, C.S., Tzovaras, D.: Understanding of human behavior with a robotic agent through daily activity analysis. Int. J. Soc. Robot. **11**(3), 437–462 (2019)

Martins, G.S., Santos, L., Dias, J.: User-adaptive interaction in social robots: a survey focusing on non-physical interaction. Int. J. Soc. Robot. **11**(1), 185–205 (2019)

McCrae, R.R., Costa, P.T., Jr., Martin, T.A.: The neo-pi-3: a more readable revised neo personality inventory. J. Pers. Assess. **84**(3), 261–270 (2005)

Moro, C., Nejat, G., Mihailidis, A.: Learning and personalizing socially assistive robot behaviors to aid with activities of daily living. J. Hum-Robot. Interact. **7**(2), (2018)

Morris, J.C.: The clinical dementia rating (cdr). Neurology **43**(11), 2412–2412 (1993)

Moyle, W., Jones, C., Murfield, J., Dwan, T., Ownsworth, T.: 'we don't even have wi-fi': a descriptive study exploring current use and availability of communication technologies in residential aged care. Contemp. Nurse **54**(1), 35–43 (2018)

Nikolaidis, S., Ramakrishnan, R., Gu, K., Shah, J.: Efficient model learning from joint-action demonstrations for human-robot collaborative tasks. In: Proceedings of the tenth annual ACM/IEEE international conference on human-robot interaction, association for computing machinery, New York, NY, USA, HRI '15, pp 189–196 (2015)

Portugal, D., Alvito, P., Christodoulou, E., Samaras, G., Dias, J.: A study on the deployment of a service robot in an elderly care center. Int. J. Soc. Robot. **11**(2), 317–341 (2019)

Raggioli, L., Rossi, S.: A reinforcement-learning approach for adaptive and comfortable assistive robot monitoring behavior. In: 2019 28th IEEE international conference on robot and human interactive communication (RO-MAN), pp 1–6 (2019)

Rossi, S., Staffa, M., Bove, L., Capasso, R., Ercolano, G.: User's personality and activity influence on hri comfortable distances. In: Social Robotics, Springer International Publishing, Cham, pp 167–177 (2017)

Rossi, S., Ercolano, G., Raggioli, L., Savino, E., Ruocco, M.: The disappearing robot: an analysis of disengagement and distraction during non-interactive tasks. In: 2018 27th IEEE international symposium on robot and human interactive communication (RO-MAN), pp 522–527 (2018)

Saunders, J., Syrdal, D.S., Koay, K.L., Burke, N., Dautenhahn, K.: "teach me-show me"-end-user personalization of a smart home and companion robot. IEEE Trans. Human-Mach. Syst. **46**(1), 27–40 (2016)

Schroeter, C., Mueller, S., Volkhardt, M., Einhorn, E., Huijnen, C., van den Heuvel, H., van Berlo, A., Bley, A., Gross, H.M.: Realization and user evaluation of a companion robot for people with mild cognitive impairments. In: 2013 IEEE International Conference on robotics and automation, IEEE, pp 1153–1159 (2013)

Tapus, A., Mataric, M.J., Scassellati, B.: Socially assistive robotics [grand challenges of robotics]. IEEE Robot. Autom. Mag. **14**(1), 35–42 (2007)

Tizzano, G.R., Spezialetti, M., Rossi, S.: A deep learning approach for mood recognition from wearable data. In: 2020 IEEE international symposium on medical measurements and applications (MeMeA), pp 1–5 (2020)

Umbrico, A., Cesta, A., Cortellessa, G., Orlandini, A.: A holistic approach to behavior adaptation for socially assistive robots. Int. J. Soc. Robot. **12**(3), 617–637 (2020)

Wagner, A.R.: Robots that stereotype: creating and using categories of people for human-robot interaction. J. Hum-Robot. Interact. **4**(2), 97–124 (2015)

Wu, Z., Deng, S., Wu, J.: Chapter 2 - service-oriented architecture and web services. In: Service Computing, Academic Press, pp 17–42 (2015)

Claudia Di Napoli got a degree in Physics with specialization in Cybernetics and she is a research scientist at the High Performance Computing and Networking Institute of CNR. She published more than 60 papers on international journal and conferences. Her main research interests include Service Oriented Computing, Software Agents, Cloud Computing, Social Assistive Robotics, Reinforcement Learning.

Giovanni Ercolano got a degree in Computer Science and a Ph.D. in Information Technology and Electrical Engineering. His Ph.D. thesis topic was the assistive robots for elderly people. His main research interests include Human Robot Interaction, Assistive Robots, Deep Learning and Computer Vision.

Silvia Rossi is currently Associate Professor at Dipartimento di Ingegneria Elettrica e Tecnologie dell'Informazione of the University of Naples Federico II, Italy. She is Co-chief manager of the PRISCA (Intelligent Robotics and Advanced Cognitive System Projects) lab. Her research interests include Multiagent Systems, Human-Robot Interaction, Cognitive Architecture, User Profiling, and Social Robotics.