Robotics and Autonomous Systems 161 (2023) 104346

Contents lists available at ScienceDirect

Robotics and Autonomous Systems

journal homepage: www.elsevier.com/locate/robot

Seeking at-home long-term autonomy of assistive mobile robots through the integration with an IoT-based monitoring system

Matteo Luperto [a,*], Javier Monroy [b], Francisco-Angel Moreno [b], Francesca Lunardini [c], Jennifer Renoux [d], Andrej Krpic [e], Cipriano Galindo [b], Simona Ferrante [c], Nicola Basilico [a], Javier Gonzalez-Jimenez [b], N. Alberto Borghese [a]

[a] *Applied Intelligent System Lab, Department of Computer Science, University of Milan, Italy*
[b] *Machine Perception and Intelligent Robotics Group, Department of System Engineering and Automation, Biomedical Research Institute of Malaga, University of Malaga, Spain*
[c] *NearLab, Department of Electronics, Information and Bioengineering, Politecnico di Milano, Italy*
[d] *Machine Perception and Interaction Lab, Center for Applied Autonomous Sensor Systems, Örebro University, Sweden*
[e] *Smart-Com, Slovenia*

ARTICLE INFO

Article history:
Received 11 September 2020
Received in revised form 2 November 2022
Accepted 18 December 2022
Available online 21 December 2022

Keywords:
Socially assistive robots
IoT
Internet of robotic things

ABSTRACT

In this paper, we propose a system that stems from the integration of an autonomous mobile robot with an IoT-based monitoring system to provide monitoring, assistance, and stimulation to older adults living alone in their own houses. The creation of an Internet of Robotics Things (IoRT) based on the interplay between pervasive smart objects and autonomous robotic systems is claimed to enable the creation of innovative services conceived for assisting the final user, especially in elderly care. The synergy between IoT and a Socially Assistive Robot (SAR) was conceived to offer robustness, reconfiguration, heterogeneity, and scalability, by bringing a strong added value to both the current SAR and IoT technologies. First, we propose a method to achieve the synergy and integration between the IoT system and the robot; then, we show how our method increases the performance and effectiveness of both to provide long-term support to the older adults. To do so, we present a case-study, where we focus on the detection of signs of the *frailty syndrome*, a set of vulnerabilities typically conveyed by a cognitive and physical decline in older people that concur in amplifying the risks of major diseases hindering the capabilities of independent living. Experimental evaluation is performed in both controlled settings and in a long-term real-world pilot study with 9 older adults in their own apartments, where the system was deployed autonomously for, on average, 12 weeks.

1. Introduction

Demographic changes in industrialized countries include increased life expectancy and reduced birth rate, leading to the ageing of the population [1]. This trend brings many challenges to society that remarkably impact on the healthcare and social systems. In such a scenario, innovative and cost-effective solutions are required to reform the delivery of care to the elderly [2].

For this reason, in recent years, a variety of assistive solutions have been developed to prolong and sustain independent living of the elderly. This is done especially by deploying remote health-monitoring functionalities in the elders' comfortable home environment, rather than in a more controlled, but also more expensive and often overpopulated setting, as the one of care homes. A variety of these solutions fall under the umbrella of Ambient Assisted Living (AAL), the use of information and communication technologies (ICT) for monitoring, stimulating, preventing, curing, and, overall, improving wellness and health conditions of older adults and patients with special needs [3]. The main goal of AAL is to preserve the independence of these people and, as a consequence, to increase safety in their home environment through technologies such as *Socially Assistive Robotics* (SAR) and *smart homes* based on the Internet-of-Things (IoT).

SAR describes a class of robots that is at the intersection of socially interactive robotics, which is focused on socially engaging and *stimulating* the user through social and nonphysical interaction, and assistive robotics, whose aim is to overcome their users' physical limitations by helping them in daily activities (such as getting out of bed, brushing their teeth, or walking) [4]. SAR robots are designed to be used in a variety of settings including clinics, nursing, and private homes.

However, despite the growing attention devoted to this field, the use of SARs in elderly care is not completely ascertained.

* Corresponding author.
E-mail address: matteo.luperto@unimi.it (M. Luperto).

https://doi.org/10.1016/j.robot.2022.104346
0921-8890/

Indeed, besides the elderly's lack of familiarity with technology, the mismatch between needs and solutions offered by the use of robots is considered as a key obstacle for SAR adoption [5,6]. Although most of modern robots have on-board sensing, computing, and communication capabilities, which make them able to execute complex tasks autonomously, these skills are often not enough to fulfill the requirements imposed by complex and unpredictable environments such as house apartments. The lack of trust and the safety concerns that arise in the elder user as a consequence of the robot's fragile autonomy have a negative impact on SARs' acceptance [7].

Smart homes are defined as ubiquitous computing applications that enable remote *monitoring* and home automation. To enhance the safety and wellbeing of its inhabitants, the house has to become intelligent with the use of environmental sensors and smart objects. Smart objects are characterized by processing power, pervasive connectivity, and the capability of detecting changes occurring in the environment. The IoT is a technological approach that leverages on the ability of smart objects and sensors to communicate with each other to build networks of things [8].

Therefore, through home-based continuous monitoring of the user, IoT-based smart homes have the potential to foster comfort, enhance safety, and provide healthcare prevention and monitoring to their inhabitants. Notwithstanding the disruptive potential of IoT technologies, collecting good, usable, and reliable data from an uncontrolled environment (e.g., a private home) to extract valid health-related indicators remains challenging [9]. As a consequence, the need of obtaining valid and reliable data from IoT-based smart home platforms becomes crucial.

The limitations that affect both SAR and IoT-based smart homes are amplified by the fact that such systems are, generally, designed to work in unsupervised and uncontrolled settings for prolonged periods of time like days, weeks, or months. However, as described in [10], a continuous autonomy, efficiency, safety, usability, and robustness of a mobile service robot for a long period of time in a house/apartment could be particularly difficult to obtain, as such environments are not specially adapted for the robot's presence. At the same time, to perform longitudinal data analysis for the extraction of valid health-related indicators, the monitoring system should be able to continuously collect reliable series of data for the same period of time.

In this framework, the creation of an Internet of Robotics Things (IoRT) [11,12] based on the interplay between pervasive smart objects and autonomous robotic systems is claimed to enable the creation of innovative services conceived for assisting the final user, especially in elderly care. The synergy between IoT and robotics was conceived to offer robustness, reconfiguration, heterogeneity, and scalability, by bringing a strong added value to both the current SAR and IoT technologies.

In this work, we present a method to create synergy and exploit the integration between the IoT system and the robot to increase the performance and effectiveness of both and to provide long-term support to the older adult, by following and extending the concept of *mutual care*, a concept based on the social dynamics of mutual-aid. This paradigm suggests that robots, which ask users for help to overcome their limitations, will support the users' perception of having a beneficial relationship (with the robot) based on mutuality [13]. This idea is similar to the "symbiotic relationship" concept defined in [14], where it is discussed how not only the robot could assist the user, but also the user could help the robot in performing some tasks that the robot is not able to perform (for example due to physical limitations, as in the presence of an obstacle, or for a failure in the robot perception, as in the case of a lost robot localization).

We propose to extend the concept of mutual care to all of the actors of our system, by creating a *mutual-aid actor-network*, where each one of the components benefits of the interaction with the others. In this way, by exploiting the synergies among different actors, we not only allow them to fulfill their individual tasks in a more efficient way, but we increase the overall effectiveness and reliability of the entire system. Within this network, and following the mutual care concept, the role of the users is particularly important as they are endowed with the dual role of both being monitored and assisted and of supporting the whole system by performing those tasks that cannot be carried on by the system itself in autonomy (as an example in case of technical failure). In a sense, and as can be seen from the diagram of Fig. 1, the user is in the center of the mutual-aid actor-network, which is developed around them. This architecture results in multiple benefits. On the one hand, the robot can use the heterogeneous network of smart objects and sensors just like its own sensors, thus obtaining a wider perception-horizon compared to local on-board sensing, in terms of space, time, and type of information. On the other hand, the robot's social component and interaction with the human user can be leveraged to facilitate and foster the collection of usable, and reliable data through IoT technologies distributed in the smart home environment. The interaction among all actors is coordinated by a cloud-based virtual agent that acts as a Virtual Caregiver.

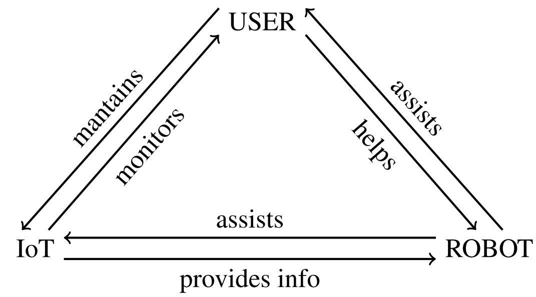


Fig. 1. The overview of the interaction between all actors of our system.

To show how such an IoRT framework can be achieved, and to experimentally evaluate its benefits, we focus on a case-study of an IoRT system specifically designed for elderly care. This system, developed within the MoveCare [15] H2020 project, is designed to work autonomously in a complex and uncontrolled environment as the apartment of an older adult living alone for a long-term period and without the direct presence of a technician or a researcher. The case–study, described in Sections 3 and 4, allows us to discuss current limitations of SAR and IoT-based monitoring platforms and to evaluate how an integrated IoRT framework can be used to overcome them, ultimately moving a step towards a robust real-world deployment. In Section 5 we evaluate the advantages of the proposed framework both in controlled experiments and within long-term pilot experiments with real users.

The main contribution of this work are three:

- we analyze the strength and limitations of IoT and SARs within a home-based AAL setting;
- we propose a novel framework where the interplay between the IoT system, the robot, and the user can overcome such limitations by both assisting and being assisted by each one of the other components. We show how it can be achieved in a case–study;
- we demonstrate, in an extensive long-term on-the-field trial with end users, the main advantages of our IoRT framework.

This contribution stems from the H2020 project MoveCare [15], which involved the development of a multi-purpose platform for elderly care. In this work, we focus on two of the components such platform, namely the IoT system and the SAR, and on the interplay between them and the user. We refer the reader to the work of [16] for a comprehensive description of the robotic platform and its performance, and to [17] for a description of the entire platform developed during the project, as these results are beyond the scope of this work.

2. Related works

An exhaustive review of previous work exploring the benefits of assistive robots in elderly care can be found in [18], where a functional distinction is outlined between *service* robots, aiming at helping users in daily activities as the one discussed here, and *companion* robots, targeting the psychological well-being of their owners.

The review highlights a trend that leverages assistive robots for health care interventions [19] within the residential living environment. Examples of these include works like [20], which proposed the use of a half-bust robot to assist the cognitively-impaired older adults during mealtime, or [21], in which an info-terminal robot was used to provide useful information and reminders to the residents of a care home. As a general result, most of the proposed solutions have proved effective in enhancing the well-being of older adults users interacting with robots.

In its turn, long-term autonomy (LTA) of assistive mobile robots is a challenging and still unexplored research topic, due to the unpredictability of potential failure causes of the robot and of the potential situations in which it may find itself [22]. The functionality required by such robots is often investigated with structured interviews, as in [23,6,24], but a few works have actually deployed such robots for real-world evaluation. Recent works like [25] have done a remarkable effort in LTA, by deploying an autonomous social robot for several weeks in settings like an assisted living facility.

Despite the established benefits of using assistive robots in the context of residential living, the ultimate goal should be the deployment of robotic assistants to the user's home for remote health monitoring functionalities. To answer this need, the integration of robots in ambient assisted living (AAL) environments has been proposed in works such as [26,27] or [28], where a tele-operated mobile robot was deployed to the older adult's home, together with a network of sensors, to achieve the monitoring of daily-life activities. However, the integration between AAL and robots discussed in such works and in works such as [11,12] is more focused to show its potential application than presenting a detailed use case of actual implementation in a real-world scenario. In our work, we provide long-term real-world data about the benefits of such a system.

A system similar to ours can be found in the series of works about the CompanionAble and SERROGA projects [29,30], which presented performance results of long-term tests in private apartments, similar to those planned for our pilot phase. In a following work of the same group, presented at [31] and developed within the project SYMPARTNER showed the results obtained in a 20-weeks field study with 20 older adults (1 week for each participant). Finally, in [32] preliminary results of the field trial of the MORPHIA project are presented, which lasted a few weeks and where a SAR is used in integration with a tablet, also assessing the performance of the platform on the field. Another recent service robot focused on fall detection and that offers other services such as reminders and entertainment suggestions is described in [33–36]. A robot and an experimental evaluation similar to ours was performed by the EnrichMe project [37,38], during which SARs were tested within the house of 10 older adults for 10 weeks to investigate their acceptability. Differently from ours, the main objective of this project was to investigate tools and functionalities that are needed for the assistance of users at home. The main differences with respect to our approach lie in the integration of the robot with IoT-based user monitoring, in providing new functionalities, in the extent and the number of robots used, and in the duration for tests with end-users.

A system composed of an assistive robot designed to provide reminders and supported by a cloud infrastructure is shown in [39]. Similarly to our work, the robot was integrated with a smart house and used environmental sensors to estimate the user's location to provide notifications to the user. In our work, we proposed a deeper integration between the IoT monitoring system and the robot. Moreover, they presented a simplified implemented scenario to show the feasibility of the system components over a cloud infrastructure to accomplish a reminder service. In our work, the integration with the IoT system of the SAR, enabled us to deploy our system in a real-world setting for a longer period of multiple weeks, in full autonomy and with a deeper interplay between the components.

The core functionalities of a system with an architecture similar to the one proposed here, that integrates a service robot, a home sensor network, a body sensor network, a mobile device, cloud servers, and remote caregivers are presented in [40]. Differently from us, results obtained in [40] are achieved in a controlled lab test-bed (similarly, in [39], the same authors present a proof of concept of the system, while we present a fully working system). Moreover, the goal of such a work is more shifted towards the evaluation of the performance of clinical data monitoring to detect ADLs.

Within the field of AAL, several works have proposed IoT-based smart homes for elderly care, such as the CASAS [41] project, which provided a non-invasive assistive home environment for dementia patients, and the Elite care [42] project, which developed an assisted living facility equipped with a variety of sensors to monitor meaningful indicators for the elderly, such as time spent in bed and body-weight. Among them, some works investigated the use of smart-home monitoring to perform early detection of early stages of mild cognitive impairment, as [43,44], and the detection of signs of frailty [45]. However, to the best of our knowledge, no other works have investigated the integration of assistive robots with monitoring frameworks for the detection of early signs of cognitive decline in the long-term.

3. Our proposed approach

This section presents the case–study of a system that integrates IoT-based monitoring system and a SAR, as described in Section 1. This system is specifically designed to monitor and assist a specific category of users, *pre-frail* older adults who live alone and that are still independent in their daily life, and that is focused on an objective, namely on the detection of signs of the *frailty syndrome* [46].

The term "frailty" encompasses a set of vulnerabilities typically conveyed by a cognitive and physical decline in older people. These vulnerabilities concur in amplifying the risks of major diseases, hindering the capabilities of independent living, and increasing the need for assisted living services or hospitalization. Frailty symptoms have been shown to be correlated to three or more warnings related to weight loss, weakness, exhaustion, slow gait, and reduced physical activity [47]. Pre-frailty refers to those subjects that are at high risk of progressing into frailty. Despite being subject to such vulnerabilities, independently-living older adults are a category of subjects relatively healthy and able to successfully interact with the technologies provided by AAL platforms.

Within this framework, the IoT-based monitoring system, described in Section 3.1, is used to *monitor* the activities of daily

Table 1
List of sensors composing the IoT-based monitoring framework. The periodicity indicates the frequency upon a certain measure should be obtained to have a reliable data.

Component	Type	Monitoring data	Periodicity
PIR sensors	passive	User presence/ADL	continuous
Door sensor	passive	User presence/ADL	continuous
Smart power plug	passive	ADL	continuous
Couch/Bed IMU	passive	sleeping /ADL	continuous
Weight scale	active	weight gain/loss	daily
Smart ball	active	maximum grip strength	weekly
Smart insoles	active	gait patterns	whenever used
Smart pen	active	tremor, handwriting features	whenever used

living (ADL) performed by the older adult to detect signs of frailty, enhance safety, and provide healthcare prevention without using wearable devices but only environmental sensors.

The role of the Socially Assistive Robot (SAR) [4], described in Section 3.2, is to (i) stimulate the user to perform an activity, (ii) provide a set of functionalities to both the user and the other components of the system, and (iii) support the older adult in case of an emergency (help).

While the details and implementation of all the components of our system have a specific target, namely the detection of frailty in older adults, the proposed architecture integrating an IoT platform and a SAR could serve as a suitable deployment for different assistive settings. As a consequence, the strengths and limitations of the two modules, and the advantages of building an IoRT-integrated system can be generalized to other domains of SARs and IoT-based AAL.

3.1. The IoT-based monitoring system

The IoT-based monitoring system is designed to collect, within the own house of the user, data of interest that can be correlated to signs of frailty [47]. The detection of these signs requires continuous monitoring of functions known to undergo alterations as a consequence of physical and cognitive decline. The monitoring system is designed to be both pervasive, to collect all the events of interest, and unobtrusive, not to interfere with the user's daily life. The choice of sensors and IoT architecture is motivated by such needs.

The monitoring system is composed of a central unity, a *concentrator* which provides connectivity to all components and ensures data consistency, a *passive-sensors network* deployed inside the house, and a set of *sensorized smart objects* that require the interaction of the users. An overview of the various sensors is reported in Table 1, as well as the periodicity required for each measure to be taken.

We provide here a description of the IoT framework, while further details and motivation behind the choice and development of the monitoring framework can be found in [15], as those details are beyond the aim of this work.

The *concentrator* is a low-power computer, customized with a Wi-Fi router and external modules for BlueTooth Low Energy (BLE) and ZigBee – for the sensor network communication – and 4G connectivity. Its role is to receive, to format, and to preprocess sensor data, before transferring them to a cloud server (via MQTT protocol). It also stores relevant information for the system's setup (e.g., the map of the environment).

A *passive-sensors network* is installed in the house to detect the user's presence (room location) and activity during the day. The sensor network comprises: (i) ZigBee passive-infrared sensors (PIR), with optimized placement to cover each room; (ii) a ZigBee contact sensor on the main entrance door, to detect the user entering/exiting the house; (iii) a ZigBee power-plug for each television, to monitor the use of the TV; (iv) BLE IMUs (Inertial Measurements Unit) placed under the bed mattress and under the sofa, to detect the user sleeping/resting behavior. For privacy reasons, the user is provided with a remote control that disables data collection.

The last component of the sensor network consists of a set of smart microphones that are installed in the house to detect predefined commands (e.g., asking the robot to come or go away) and, most importantly, to provide assistance to the user in case of emergency. Microphones are placed in several rooms, so that any user's utterance can be detected from at least one of them (this requires, on average, two/three microphones for an apartment of three/four rooms).

An important component of the IoT monitoring platform is a set of four sensorized *smart objects*, crucial to monitor relevant indicators connected to frailty. These objects collect data about the user's behavior only when they are actively used by the participant. The first object is a *weight-scale* that is connected through BLE to the concentrator and is used to monitor changes in the user's weight. The user's maximal grip strength (an important factor of frailty) is monitored through a *smart sensorized anti-stress ball* [48]. The ball is used as a control input for a digital game played on the television, which guides the older adult to exert the maximal force, thus guaranteeing the reliability of the measure. The third object is a pair of *smart insoles*, to be placed inside the user's shoes. Smart insoles collect relevant gait indicators while the user walks outdoors, since data collection is automatically activated when the user exits the house [49]. Finally, a *smart ink-pen* – enriched with motion and force sensors, and storage and communication capabilities – is used to transparently monitor the user's handwriting, which represents an effective marker to detect physical and cognitive age-related alterations [50].

For a full list of the monitoring functionalities of the system, please refer to [17].

3.1.1. IoT limitations

Although the current IoT-based system was designed together with technical and clinical experts, it still suffers from the limitations that inherently characterize every IoT–based monitoring system with a similar architecture [3] when deployed in an uncontrolled environments, such as the user's private house. More precisely, in these types uncontrolled environments, the continuous collection of good and reliable data to extract valid health-related indicators remains a challenge in terms of *data availability* and *reliability*.

Data availability regards the fact that the system should be put in the condition to effectively collect this data. However, a sensor network composed of several different objects in an uncontrolled scenario could be exposed to environmental conditions that can ultimately result in a lack of (some of the) data. Smart objects data should be regularly collected on a daily or weekly basis for longitudinal analysis [48]. The availability of a measurement may be prevented by several unexpected conditions which are beyond the control of the system; examples of that are the case when the older adult does not use the object, the older adult uses the object with a lower frequency than required, a sensor is moved outside the communication range, a sensor is obstructed by an obstacle, or a sensor is out of power.

In principle, the system can be equipped with the ability to detect missing data; however, the exact cause for a missing measurement cannot be identified and, most importantly, the system has a limited capacity to undertake a fix.

Data reliability regards the fact that often measurements should be performed following a prescribed protocol, and in a controlled condition. Over a time span of multiple weeks, measurements could be subject to oscillations and even to abrupt changes. However, in the same time span, events that are outside the control of the system, such as a friend or a child relative of the older adult visiting them and trying some functionalities and objects of the system, could happen. The system should distinguish between anomalous readings that are due to a malfunctioning or an anomalous event, from the genuine changes in the measured phenomena that may be due to the deterioration of the older adult's psycho-physical condition. Moreover, oscillations in measurements do arise because of natural intra-subject variability. However, these oscillations may also be due to the fact that the user is not strictly following a prescribed protocol that is needed in order to obtain a reliable measure. As an example, the measurements collected by the daily use of a weight scale performed in the same conditions (e.g., before breakfast and with no clothes) can be affected by changes of such conditions. However, these different situations cannot be controlled by the sensors themselves.

In Section 4 we show how the use of a SAR could be an enabling technology to reduce such limitations and to provide more robust and effective monitoring of older adults living alone.

3.2. The robotic platform

The mobile robot platform that we used in our case-study, Giraff-X, was developed within the MoveCare project, starting from the telepresence robot Giraff, a robotic platform progressively developed for HRI with older adults for Ambient Assisted Living (AAL) and used in ExCITE [51,52], FP7 (GiraffPlus [28]). The Giraff-X is equipped with a set of vision and time-of-flight sensors, as well as with an additional GPU, to perform long-term, autonomous navigation within the older adults' houses. An image of the Giraff-X robot can be seen in Fig. 2. The hardware specification of the robot, i.e., a human-sized differential-drive robot equipped with RGB or RGB-D camera and a laser range scanner, as well as its main functionalities, are common to other robotic platforms used for AAL, such as [35,38,31,32,25]. For this reason, the strengths and limitations of our SAR platform itself are general to those of similar platforms. For a full description of the robot software and hardware architecture, please refer to [16].

3.2.1. Robot functionalities

The core capability of the robot is to move autonomously in a house to search and interact with the user via speech. At the same time, the robot should be able to maintain its operational state. At setup time, the robot navigates inside the house creating a 2D map. This map is annotated with the positions of the sensors and of the rooms. To improve navigation across narrow spaces, a navigation assistant has been developed [53] that detects problematic areas in the environment and automatically generates a set of auxiliary navigation waypoints. The locations that the robot should reach during operation are defined as *nodes* in a topological map of the environment (see Fig. 3). Such nodes are manually placed on the map at installation time in relevant destination points and represent all the positions where the robot can navigate to interact with the user. While moving from one node to another, the robot can execute any trajectory, according to its path planner. Note that some rooms will not contain a node (e.g., hallways), as the robot will not perform any activity there, while others will have more than one if they present more than one interesting position (e.g., at the two sides of a table).

To interact with the user, the robot is equipped with a vision-based module to detect the user's position, and to safely approach them attending to obstacles and proxemic rules. HRI is performed through a multi-modal interaction system composed of voice and visual interfaces, as well as two action buttons to get user feedback. The main communication modality of the robot is through

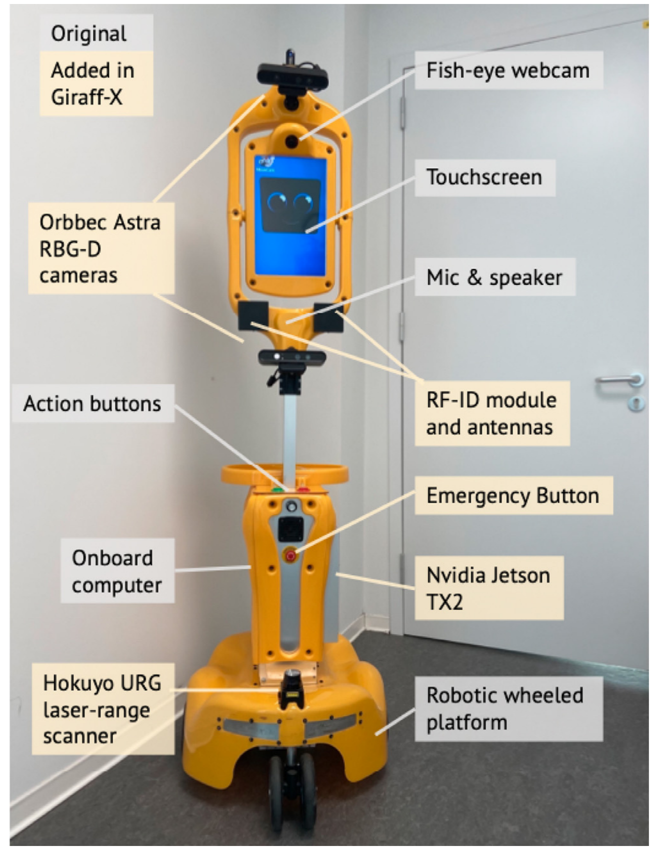


Fig. 2. The Giraff-X mobile robot.

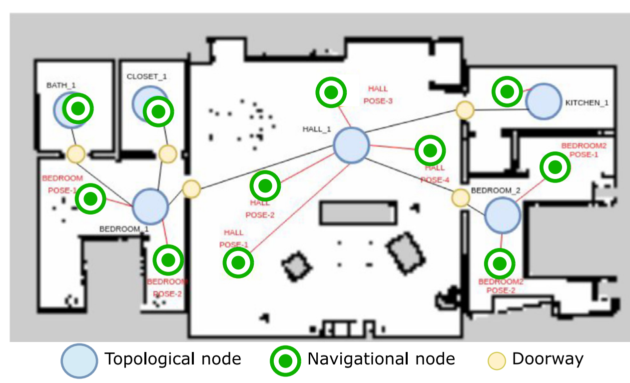


Fig. 3. Example of a topological map built upon the robot-generated occupancy grid-map of a real apartment. Each room is designated with one topological node, while multiple navigational nodes may be used according to the dimensions and furniture present in it.

speech (both by speaking and listening to the users' answers). The communication of the robot with the other components is by sending and receiving messages and commands through MQTT. Finally, a vision-based navigation procedure has also been implemented to perform autonomous docking [54].

3.2.2. Robot interventions

The robot, as the main actuator of the system, is able to perform a set of *interventions* upon request. During normal operation, Giraff-X awaits at the docking station. When an intervention is requested, the robot undocks (if necessary) and then starts searching for the user by navigating to the expected user location. If the user is not found there, it performs a search over the whole

Fig. 4. Pictures of different apartments where the Giraff-X robot was installed. As can be seen, different flooring types, cluttered areas, and narrow doorways are common in these environments, making autonomous navigation a challenging task.

house. Once the user is found, the robot approaches and interacts with the user to perform the target intervention, provides the user's response to the system, and returns to the docking station if no other interventions are planned.

The interventions required by the system are triggered according to a schedule or knowledge inferred from the data collected by our platform. They are conveyed as *reminders*, where the user is asked to perform a task (e.g., measure their weight for monitoring), or *invitations*, which inform the user about the possibility to perform an activity such as going out for a walk. The robot can also perform more complex interactions with the user, as explained in [55]. Moreover, the user can directly trigger the robot by asking for the *help* service, where the user calls for help and the robot finds them, confirms the emergency, and establishes a communication with the caregiver, who can subsequently activate a video call or even take remote control of the robot. More details about the robot's role in this scenario are provided in Section 5.

Finally, the robot can maintain a proper autonomy level with battery management, performing auto-docking if it has been idle for a long time or its battery level is critical. For a full list of the robot interventions and more details of their implementation, which are beyond the scope of this work, please refer to [17,16].

3.2.3. SAR limitations

One of the biggest challenges of developing a truly autonomous assistive robot is to ensure long-term robustness and reliability [16]. Apartments are particularly challenging environments, as can be seen in Fig. 4, and are dynamic (e.g., people moving, day–night changes, moving obstacles and furniture), hence leading the robot to react to changing task conditions through time. Moreover, due to the presence of narrow passages (e.g., doorways — see Fig. 3), the robot might find difficulties operating within the environment, even incurring in navigation failures. Despite the fact that *ad-hoc* navigation techniques such as [53] can increase the robustness of the robot navigation, a long-term deployment of multiple weeks inside such a challenging setting could result in several situations where the robot needs to be recovered as it is blocked by an obstacle, is unable to compute a feasible path to return safely to the docking station, or it has lost its localization [25]. In principle, the robot could ask the user for help, or signal the issue to a technician, similarly to what has been done in [25]. However, repeated robot failures may jeopardize the overall effectiveness of the entire system, as it results in lower acceptability, ultimately leading to the rejection of the whole system by the user.

In the following, we show how the integration of IoT-based monitoring data can increase the robustness of a SAR towards a long-term application in actual AAL frameworks.

4. Integrated platform

In this section, we present the integration between the IoT-based monitoring system and the Giraff-X SAR through an external component that collects the data provided by both actors, analyzes them, and coordinates the system in order to react appropriately. This integrative component, a digital actor denoted as *Virtual Caregiver* (VC), is a cloud-based reasoning-system, which stores and processes all data collected by all physical actors, overseeing and coordinating all the components of the system.

The VC infers activities beneficial for the user from gathered data [56], as well as the most appropriate timing to carry them out. In this sense, activities can be promoted or initiated directly by the MoveCare framework. The VC is responsible for tuning the frequency and timing of these interventions, in order to find a good balance between their effectiveness and their acceptability [57]. The VC is also in charge of collecting all the information obtained through monitoring, which is performed at different levels of granularity. If monitoring data is missing, or additional data is needed, the VC can consequently suggest to the user to perform an activity whose output is used to collect the required monitoring data. Requests from the VC are provided to the user by the robot in the form of *interventions* through dedicated MQTT messages. The robot executes them, and reports the results of their execution back to the VC, who acts accordingly. The decision on which intervention to perform and when, is left to the VC, which is also responsible to handle unexpected situations (e.g., the user leaves the house while the robot is performing an intervention and therefore must reschedule it).

Next, we detail the impact of this framework on the two main actors, that is, the mobile robot and the monitoring system.

4.1. Impact on the robot LT-autonomy and performance

The mutual-aid care-network can greatly improve the robot capability to effectively perform complex tasks, and improve its long-term autonomy. Concretely, we make use of the environmental knowledge that is collected through the IoT network for monitoring purposes and later processed by the VC. There are two main factors that impact the robot's long term autonomy, namely *augmented knowledge* and *functional decentralization*.

Augmented Knowledge. Thanks to the data collected from the IoT-based monitoring system the robot can augment its perception capability by using the data obtained by the distributed sensor network that covers the entire environment. More precisely, the VC collects all the data received from PIR sensors, pressure sensors on bed and couch, and door sensors. Then, it provides to the robot a real-time estimated position of the user at home. The benefits of this augmented knowledge are mainly three:

1. **Efficiency**: the robot becomes more efficient by executing its tasks in a shorter amount of time. As the expected user location is continuously being reported [56], upon a new intervention the robot can go directly to the expected user location without doing a full search of the entire environment. Moreover, it must be noticed that a robot that is able to promptly locate the user without doing a full-search of the environment notably improves its expected usefulness from the user perspective, as it could be perceived as more responsive and intelligent, thus increasing its acceptability. Similarly, upon the scenario where an intervention is triggered while the user is not at home, it will prevent the unwanted event of the robot moving inside the apartment without user consent.
2. **Robustness**: in general, the robot executes interventions by traveling a significantly shorter path as it knows the expected user location. This also reduces the overall time spent navigating, thus limiting the risk of the robot facing complex situations with high chances of navigation failures [58]. Moreover, the robot can respond properly under the likely situation in which the user is moving between different rooms while the robot is trying to perform the intervention. Despite its sensing capabilities, it is likely that the robot, relying only on its own sensors, will lose track of the user at some point.
3. **Functionality:** additional and more complex tasks can be included to the robot functionalities enabled by the use of the monitoring data. For example, the robot can answer to a user's request received by a smart microphone like "come here" or "help".

Functional Decentralization. The proposed system architecture, with the robot as the main actuator and the VC as its AI, enables a light-weight robot architecture. The latter implies that reasoning about the daily schedule of the robot, about the user location, or about the reactions upon the user's actions are delegated to an external entity, the VC. This allows the robot to employ all its computational capacity to the vital tasks of autonomous navigation, obstacle avoidance, self-localization, and user interaction, increasing their robustness and, consequently, improving the robot autonomy. The latter is in line with the recent trends in cloud robotics [59,60] as on-board computation entails additional power requirements which may reduce operating duration and constrain robot mobility.

4.2. Impact on the IoT monitoring system

In this section, we show how the presence and the interaction of a socially assistive mobile robot can be used as an enabling technology for increasing control, availability, and reliability of the collected data. In this sense, the robot is used as a support mechanism for the IoT-monitoring system. Next, we highlight three scenarios of this collaboration, where it must be noticed that the embodiment of the robot for such tasks remarkably increases the effectiveness when compared to other HCI methodologies [61] that can be used to establish a direct channel from the IoT-based system to the user.

Mutual Care. Thanks to the elements in the proposed system, a mutual care relationship is created between the user, the monitoring system and the robot. In this way, the system can encourage the user of taking care of its functionalities, ultimately increasing its capabilities to take care of the user by monitoring them. This is performed by using the robot to perform reminders, asking the user to carry out small maintenance tasks (e.g., recharge a smart object, change the battery of a sensor) or using the shoes with smart insoles when going out. Those reminders are scheduled and triggered by the VC with the goal to improve the data collected and also to tackle issues that may compromise the availability of monitoring data. Examples of this type of intervention provided by the robot for our case–study are reported in Table 2 with the label MC. Finally, it must be noticed that the mutual care relationship is also extended to the robot itself. That is, the robot can directly request for help to the user in case of localization or locomotion issues.

Proactive Monitoring. Proactive behavior involves creating and controlling a context, rather than just reacting to events. In this context the system can take initiatives, by exploiting the robot, to gather monitoring data more efficiently and stimulate the user. This scenario is particularly useful when smart objects are involved (e.g., the sensorized smart pen, the smart ball, or the weight scale), as the system selectively asks the older adult to use an object whose monitoring data have not been acquired in the last period of time or to enforce the collection of periodic data on a daily or weekly basis.

Examples of the interventions provided by the robot are reported in Table 2 with the label PM.

Anomaly Detection and Data Reliability. All the monitoring data are properly recorded and analyzed in order to infer meaningful trends about the user. In this process, data integrity and validity is also checked to detect anomalies. For example, if an external person uses the weight scale (as in the case of friends or relatives visiting the older adult), it will likely trigger an anomalous reading. The system reacts to unexpected readings by asking the user to perform an additional measurement. Within this framework, the robot is the one in charge of politely requesting the older adult to repeat the measurement given the system has detected an anomaly. Moreover, the robot can suggest the user to perform a measurement following a correct protocol with timely interventions (e.g., by asking the users to perform a weight measurement after the system detects they woke up). It is important to notice that this human–robot interaction is very positive as users feel that the system is really taking care of them, notably improving acceptability of the whole framework. Examples of interventions provided by the robot are reported in Table 2 with the label AD.

5. Experimental evaluation

This section evaluates the mutual benefits that result from the integration of an IoT-based monitoring system with an autonomous SAR by conducting several real-world experiments.

Three scenarios are presented: (i) a controlled lab environment, designed to measure the performance of the system quantitatively, (ii) a real apartment within an assisted living facility, allowing us to assess the robustness of our framework under the sources of uncertainty that are linked to such environments [10], (iii) a long-term deployment of the proposed system corresponding to a pilot experiment of the H2020 project MoveCare.

All experiments have been performed using the Giraff-X robot in the configuration described in Section 3.2.

5.1. *Exp. 1*: Quantitative evaluation under a controlled setup

This experiment compares a system where the mobile robot is integrated with the IoT-monitoring network (`SAR+IoT`) to another one where the robot does not exploit such an integration (`SAR`). Reliability, robustness and performance are analyzed in both scenarios to evaluate the differences and draw conclusions.

The working scenario is a controlled laboratory environment within the premises of the University of Málaga. It is composed of an open space where a 4-room apartment (three rooms connected to a main hallway) is recreated. Furniture was used to

Table 2
Examples of the interventions performed by the robot in order to support the monitoring data.

MC	Event Intervention Result	An object is out of battery The robot asks the user to recharge the battery The user recharges the battery
MC	Event Intervention Result	An object/sensor is not providing data The robot asks the user to check the object/sensor The user fixes the issue or calls a technician
MC	Event Intervention Result	The user has not placed a smart object in its charging station The robot asks the user to put the object in the correct position The user fixes the issue or calls a technician
MC	Event Intervention Result	The robot cannot move The robot asks the for support The user brings the robot to the docking station or calls a technician
PM	Event Intervention Result	The system needs a measurements obtained from a smart object The robot suggests the older adult to use the smart object Data are collected and analyzed by the system
PM	Event Intervention Result	The system needs a daily/weekly measure from a sensor/object The robot reminds the user to use the object Data are collected and analyzed by the system
PM	Event Intervention Result	The system has no recent data on outdoor activities The robot suggests the user to go out for a walk using smart insoles Data are collected and analyzed by the system
PM	Event Intervention Result	The system needs data about maximum grip force The robot suggests to play a game with the smart ball Data are collected and analyzed by the system
AD	Event Intervention Result	An anomalous reading is collected from a sensor/object The robot suggests to take again the measurement Data are collected and analyzed by the system
AD	Event Intervention Result	A sensor provides anomalous readings The robot suggests to check the sensor and take the reading The user fixes the issue or calls a technician
AD	Event Intervention Result	A changing trend is detected in a sensor signal The robot suggests to check the sensor and repeat the reading The system detects a measurement change and acts accordingly
AD	Event Intervention Result	A measurement should be obtaining following a prescribed protocol The robot reminds the user to follow the protocol with a timely int. The user performs the measurements correctly

MC stands for Mutual Care, PM for Proactive Monitoring and AD for Anomaly Detection.

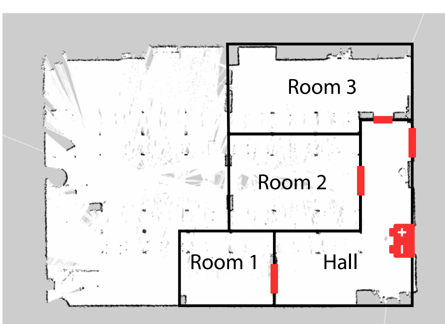


Fig. 5. The map of the simulated 4-rooms apartment were tests were performed inside an open-space lab. The red sign indicates the location of the docking station, while entrance to different rooms area highlighted in red.

divide the different rooms so that the robot was not able to perceive elements in one room from the others. The map made by the robot and the layout of the corresponding rooms used for the experiment can be seen in Fig. 5. Three PIR sensors, one for each room, were installed and, for each test, the robot started from its docking station, which is represented by a red battery symbol.

The testing functionality used for this experiment is "search for the user", a standard type of intervention that the robot is designed to perform during its operational activity and which is at the core of all interactions between the robot and the user. In the SAR+IoT setting, the robot is continuously being notified (by the VC) about the expected user location, inferred from the IoT data. Conversely, in the SAR configuration the robot has to search for the user visiting all the rooms following a predefined search pattern. For the current experiment, the search order was to start searching for the user in Room 2, then move to Room 3, and finally moving into Room 1. Two scenarios are analyzed next. First, we consider the scenario where the user does not change its location during the duration of the robot intervention (the search process), and then we account for a likely situation where the user moves inside the apartment during the search.

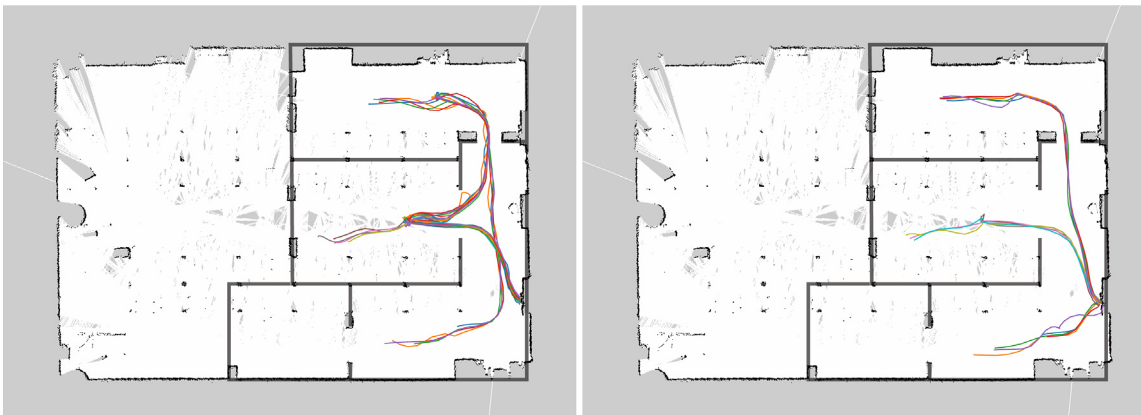
5.1.1. ***Exp 1a**: Searching for a static user*

This experiment captures the operative case where the robot searches for an user that is not moving around, like for example when watching the television on the sofa or cooking in the kitchen. Fig. 6 shows the paths followed by the mobile robot during this experiment for a total of 15 runs for each configuration, that is with and without integration between the mobile robot and the IoT monitoring system. A manikin sitting on a chair was used to embody the user, while its location was changed across different runs as follows: in the first 5 runs the dummy was at Room 1, in the second 5 runs at Room 2, and in the last 5 runs at Room 3.

Table 3 (first row) summarizes the results of this illustrative experiment, reporting the mean $\pm$ the standard deviation of the time employed by the robot to locate and approach the user and the total navigated distance, as well as the success rate. As it can be seen, given the simplicity of the experiment, the success rate rises to 100% both in the SAR setting where the robot only

Table 3
Results of Exp. 1 – controlled lab environment – where the mobile robot is commanded to search for the user. The first row depicts the results when the user was standing at a fixed location for the duration of the search, while the second row shows the results when the user is moving between different locations. t is the time required by the robot to fulfill the tasks, d the distance traveled by the robot, and *SR* represents the success rate (if the robot was able to identify and approach the user). The gain column indicates the speed-up % in time and distance traveled by the robot.

	SAR			SAR+IoT			gain	
	t (s)	d (m)	SR (%)	t (s)	d (m)	SR (%)	t (%)	d (%)
Exp. 1a: User Static in a Room	145.96 ± 71.48	13.88 ± 6.55	100%	58.39 ± 14.15	6.02 ± 2.53	100%	60.00	56.68
Exp. 1b: User Moving Between Rooms	291.68 ± 9.65	23.62 ± 1.13	0%	88.61 ± 45.65	5.87 ± 2.73	100%	69.00	75.12



(a) SAR (b) SAR+IoT

Fig. 6. Paths executed by the mobile robot during Exp. 1a (15 runs). (a) the robot operates only with the information provided by its on-board sensors, and (b) when it is aware of the user location beforehand thanks to its integration with the IoT monitoring system.

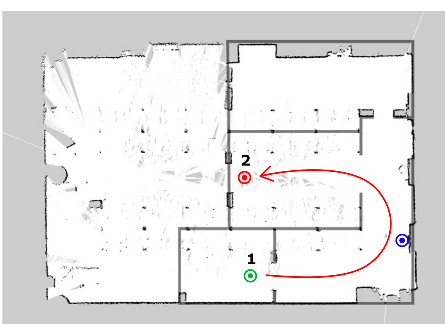


Fig. 7. Schema of Exp. 1b: The user moves from Room 1 (in green) to Room 2 (in red) while being approached by the mobile robot. The robot (starting from the blue point) has to identify and approach the user while this moves across different rooms.

relies on its own data, and in the SAR+IoT where it has access to IoT-based data. However, a clear increase in the performance can be appreciated when making use of the IoT-based data (i.e., the estimated user location), saving about the 60% of the required time and traveling half of the distance when compared to the SAR scenario. Moreover, the standard deviations of both distance and time required are lower when using the IoT-based data. The latter can be interpreted as an improvement in robustness and reliability of the system, being more consistent across different runs.

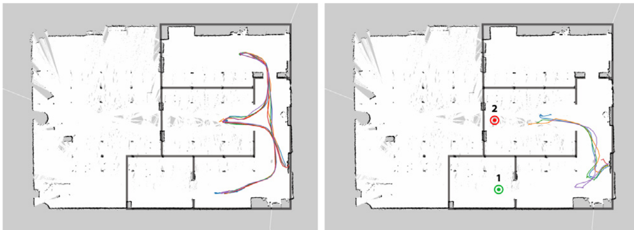
A similar conclusion can be reached concerning the trajectories performed by the robot during the search and approach to the user (see Fig. 6). The SAR+IoT configuration exhibits more direct and shorter paths towards the user, reducing the set of potentially problematic movements [53] like traversing doors or narrow spaces, and therefore improving the overall robustness of the system and in particular of the mobile robot.

5.1.2. ***Exp. 1b**: Searching for a user moving across different rooms*

In this second test, we consider a more challenging scenario where the robot is commanded to search for a user who is moving across the different rooms of the apartment (e.g., the user is doing the dishes and, at some point, goes to the living room to rest on the sofa). The robot requires a few seconds to identify and approach to the user, yet we assume that the user is not waiting for the robot to perform the action but keeps moving at their will. Eventually, the user will be at its target location, and only then the robot will be able to fulfill its task. Consequently, in this experiment we force the robot to search for the user across different rooms; if the user is identified but the approaching action is not completed, the robot resumes the search.

We created this scenario as follows: the user starts the test in Room 1, and after fifteen seconds they starts walking towards Room 2 where they will remain till the end of the experiment (i.e., upon being detected and approached by the mobile robot). Fig. 7 shows a schema of this experiment. For this experiment we carried out five repetitions for SAR and SAR+IoT, respectively.

Fig. 8 depicts the paths executed by the mobile robot during this experiment, while a quantitative comparison is provided in Table 3 (second row). As it can be seen, for the SAR configuration the success rate drops considerably, with a Success Rate (SR) that drops to 0%. The reason is that, under this setup, the robot follows a predefined search path (Rooms 2-1-3) which is opposite to the user movement (Rooms 1-2). We stress that the latter does not avoid the robot detecting the user while moving, but in all such cases it was unable to perform the approaching action in time as such an action requires the user to be in a static position for a few seconds. Upon losing the user, the robot resumes the search but does not restart it, that is, it does not re-visit a previously visited room, leading to failure. More importantly, during all the five runs the robot performed a full-search of the entire apartment before declaring that it could not find the user. The latter required large execution time and traveled distance. On the contrary, when using IoT-based knowledge (SAR+IoT) the robot starts traveling



(a) SAR (b) SAR+IoT

Fig. 8. Paths followed by the mobile robot during Exp. 1b (5 runs). (a) the robot operates only with the information provided by its on-board sensors, and (b) when it is aware of the user location thanks to its integration with the IoT monitoring system.

towards Room 1, but as soon as the user moves and triggers the PIR sensor on Room 2, the robot also changes its goal and corrects the trajectory (see Fig. 8(b)). Again, in many runs the robot was able to detect the user while moving across rooms but, as the user did not stop, the approaching action was unsuccessful and the robot had to resume the search until it finds the users. Eventually, the robot identified the user successfully in all SAR+IoT runs.

The sharp difference in SR during Exp. 1b is the fact that the robot in the SAR+IoT condition was able to observe the user's behavior even when the user was in another room, hence obtaining the time to promptly react to their actions and approach them after a detection. Conversely, the robot in the SAR–condition was always a few steps behind each user's action.

These results demonstrate how the use of the IoT-based knowledge enables the mobile robot to perform a complex task that, either could not be fulfilled or would take a very long time. Overall, the differences between both configurations are significant, both in time and traveled distance. This is really important when considering the limited power resources of a mobile robot, notably degrading its operational time and harming the functional capability towards the user.

Finally, it must be emphasized that better robot performance provides positive side effects by increasing its acceptability in the long term. The user perceives that the overall system is working properly and it minimizes the interference with their daily activities, also avoiding critical behavior such as the robot moving inside the house when the user is not present.

5.2. *Exp. 2: On-the-field test of a critical intervention*

This experiment aims to assess the ability of the proposed framework to perform one of the most critical services provided, namely to support the user in case of an emergency situation [62, 63]. More concretely, the scenario entails a *request for help* from the user which is carried out through microphones installed in the environment. Upon such a request, the system immediately sends the robot to search for the user in order to confirm the request for help and avoid false positives. When the user is found, the robot interacts with the user [64] employing voice communication to confirm the request. Either the user confirms, or they does not respond at all (i.e., they could be unconscious or in a location not accessible for the robot as in the bathroom) the system continues with the request contacting a list of predefined caregivers through a phone call. Caregivers are enabled to remotely control the robot through a teleoperation session, so that they can use the robot to assess and handle the emergency situation. In this scenario, the integration between the IoT-based monitoring system and the mobile robot is particularly important as it first enables the robot to detect the emergency request even if the user is in a different room than the robot and,

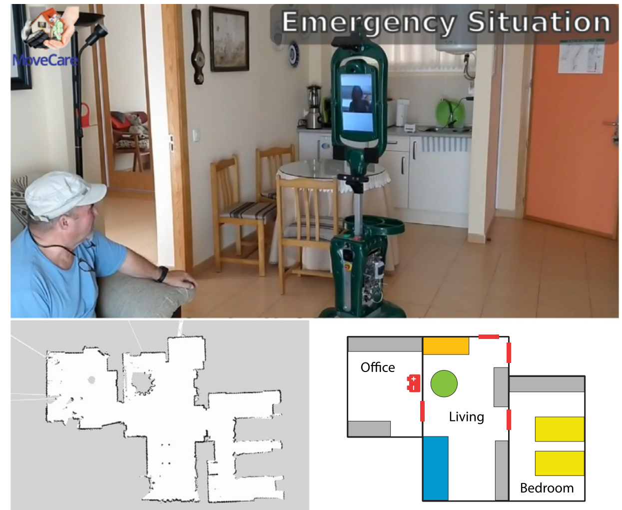


Fig. 9. (top) Picture of the Giraff-X mobile robot deployed in a real apartment during a *call-for-help* intervention. (bottom-left) The occupancy gridmap generated by the robot for navigation and (bottom-right) the floor plan of the apartment. Beds are displayed in yellow, the kitchen in orange, the table in green and the sofa in blue. Other furniture is highlighted in gray. The docking station is represented with a red symbol and doors are represented by red squares.

most importantly, to promptly react in this potentially critical situation.

Tests were performed in an apartment inside the Assisted Living Facility of Servimayor, Losar de la Vera, Extremadura, in Spain. The apartment is composed of three rooms (an office, a living room with a sofa and a small kitchen, and a bedroom) plus a bathroom, which was closed during the experiment and not used for privacy reasons. Two PIR sensors were placed in the living room, one in the bedroom, and one in the office. Pressure sensors were placed on the couch and under the beds, while a door sensor was used to detect the event of users entering/exiting the premises. Two microphones were installed, one covering the bedroom, while the other one covered the living room and the office. Fig. 9 shows a picture of the apartment together with a schematic view of the rooms and the occupancy map built by the robot.

The call for help functionality was tested 10 times, changing the user location along the repetitions. In the first 5 runs the user was located in the living room, sitting at the kitchen table, on the armchair, lying on the sofa, standing against the main door, and lying on the ground, respectively. In the last 5 runs the user was located in the bedroom, sitting at the first bed, at the second bed, standing between the first and the second bed, standing behind both bed, and lying on the floor, respectively.

The robot successfully detected and approached the user in all the tests, employing and averaged time of 96.20 ± 24.68 s (under 2 minutes in all runs). This time represents the interval from the starting of the request for help (when the microphone detects the user request) till the confirmation of the user, that is, after the robot has identified and approached them, asked for confirmation, processed correctly the spoken reply, and provided also a voice feedback to the user.

These results demonstrate the maturity of the system when facing a critical intervention in a real environment, and underline the importance of integrating the monitoring system with the robot in order to improve its efficiency and reliability, these are fundamental aspects when the safety and the security of elders could be at stake.

Table 4
List of weight measurements for each user during the Movecare Pilot.

	Users								
	01	02	03	04	05	06	07	08	09
Robot	✓	✓	✓	✓	✓	✗	✗	✗	✗
Weeks	12	15	12	10	12	17	13	10	7
WM	52	22	6	46	9	32	15	6	9
REM	33	29	26	21	34	–	–	–	–

robot indicates if the system installed for that user included the robot or not. *Weeks* indicates the total pilot duration for each user. WM indicates the number of weight measurements performed by the user and REM indicates the amount interventions performed by the robot to remind the user to perform a weight measurement.

5.3. ***Exp. 3***: *Long-term impact on the IoT monitoring data*

This experiment evaluates the impact of integrating a mobile robot with the IoT monitoring system in real scenarios. The data presented was gathered during the pilot phases of the MoveCare project, where the described system was installed inside the house of 9 older adults participants for a total of about 27 months combined.

We present here a comparison between two configurations of the MoveCare framework (which consists of other actors besides the IoT-based monitoring platform and the mobile robot reported here, see [15] for more details). The first one only considers the IoT-based monitoring system (IoT), while the second configuration also includes the Giraff-X mobile robot within the apartment (SAR+IoT).

Overall, the system was installed inside the apartments of 9 older adults living in Milan (Italy), of which 5 of them included the mobile robot. Moreover, 7 of the pilot users lived in private apartments while the other 2 were living during the pilot duration in an independent apartment inside an assisted living facility. Each user, due to their availability, participated to the study for a different number of days. On average, each older adult had the system in their apartment for 12 weeks and robots were functioning, cumulatively, for 400 days inside user's apartments. The duration and setting of the experiment for each user is described in Table 4.

We focus our analysis on the role played by the mobile robot when obtaining reliable measurements from smart objects: the smart-ball, the smart-pen, and the weight scale. Discussion and evaluation of the validity and use of monitoring data for detection of frailty signs are beyond the scope of this paper and are discussed in [17]. Table 4 summarizes the number of times the users measured their weight during the pilot for both configurations, IoT and SAR+IoT. As it can be seen, the system was able, on average, to collect more measures for the user with a robot (53 ± 39) in comparison to those without it (31 ± 20). Not only the robot encourages the users to actively use the smart objects on a regular basis, but also informs them (Reminders) in case incorrect values are measured or when the users failed to comply with the agreed protocol (i.e., to measure their weight in the morning after getting up), suggesting them to repeat the measurement.

A particular case is User-03 (*with robot*). This user performed only 6 weight measurements during a 12 weeks period. Yet, the robot reminded the user several times to perform the weight measurement, a situation that lead the user to signal to the technicians a possible fault on the weight scale, as the user was trying to perform the weight measurements as requested by the robot, but without success. Thanks to this, we discovered that the weight scale installed at the house of User-03 was faulty, and needed to be replaced. However, due to the lock down in place for the COVID-19 pandemic, this was not possible and, consequently we were not able to collect weight measurements for that user. (If we consider User-03 as an outlier, the average of WM performed by users *with robot* is of 65 ($\sigma = 36$)). A similar event happened to User-05. This user was performing regularly weight measurements also following the protocol and, consequently, received few reminders from the robot. After a few weeks, an update on the firmware of a component (concentrator) caused an issue with the BLE connectivity, which ultimately resulted in a malfunctioning in the weight scale. The system consequently performed daily interventions due to missing data. The user signaled the issue to technicians, which were able to remotely detect the problem and fix it. Despite the aforementioned problem, we indicate this use case as a good example of the positive effect of a mobile robot integrated with an IoT-based monitoring system, as we were finally able to detect and fix anomalies in the monitoring platform.

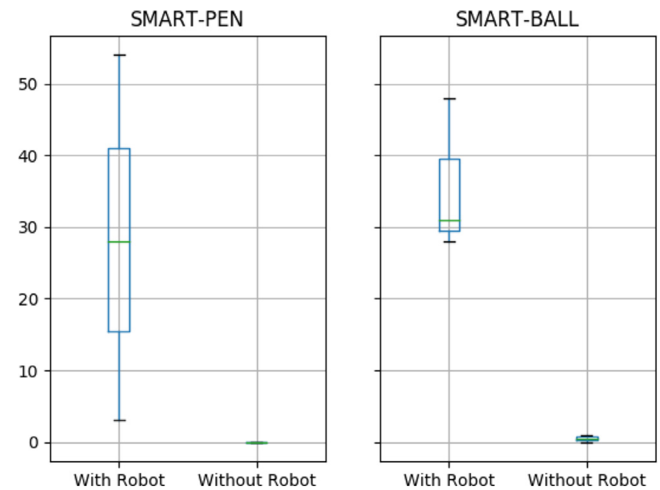


Fig. 10. Average number days of use of the smart-ball and smart-pen smart objects for pilot users *with robot* and *without robot*.

Similarly, Fig. 10 shows the boxplot corresponding to the number of times older adults with and without robot used the smart-ball and the smart-pen, respectively. These plots demonstrate the great impact of a mobile robot to encourage users to actively use smart objects (and consequently to gather health monitoring data). It can be seen how only older adults with the robot used the sensorized objects on a regular basis. This is due to the timely and appropriate reminders given by the mobile robot cohabiting with them, something that seems to be remarkably relevant for long time deployments. It must be stressed that on apartments where no robot was installed, the system was still able to send notifications to the user through a tablet to suggest the use of sensorized objects [57]. However, the embodiment of the robot [61] resulted into more effective actions. These results show how the role of the mobile robot is particularly important within an AAL framework, as it can provide a method to interact with the user (through embodiment) and to trigger a specific action.

5.4. ***Exp. 4***: *Long-term autonomy of the SAR*

This section evaluates the performance of the proposed system to provide interventions and reminders to users in a real scenario. The data presented here correspond to the same pilot study described in Section 5.3 and are used to evaluate the ability of the proposed system to guarantee robustness and high performance to a long-term deployment of a SAR into a complex and uncontrolled environment.

Table 5
Performance of the robots in the pilot described in Section 5.3 for providing reminders to five users inside their own houses during a time of 12 weeks each.

Intervention outcome	Description	#	SR (%)	#	SR(%)
User found	Performed with success	494	89.49	535	96.92
	User approach issues	32	5.80		
	HRI issues	9	1.63		
User not found		17	3.1	17	3.1
Intervention not performed	System offline	31	4.69[a]	109	16.49[a]
	Emergency button pressed	15	2.23[a]		
	User outdoor	63	9.53[a]		

[a]Data are relative to all interventions requested by the system.

We present here the performance of the SAR in searching, identifying, approaching, and interacting with the users during a period of 12 weeks. Data are gathered for User-[01-05], which, as listed in Table 4, were those with the Giraff-X SAR. In the 40% of the interventions considered, the robot required an answer from the user (as yes/no). In the other interventions, considered, the robot approached the users and talked to them without requiring any answer. We do not report results obtained with other interventions and functionalities performed by the robot (described in Section 3.2), as those are beyond the scope of this work and are discussed in [17,16].

Overall, the system requested the robots to perform 661 reminders; the robots attempted to perform 552 of them while, for the rest, the robots did not performed any intervention as either the robot emergency-button was pressed, the system was turned off by the user, or the user was outdoor. Note that the system does not trigger any intervention when the user is not at home, but users may leave the house after an intervention is scheduled but not executed. In that settings, the system reacts and the robot prevents the execution of the intervention. A summary of the interventions performed is reported in Table 5 and in Fig. 11. It can be seen how the robot was able to correctly identify the user in the 96.92% of the interventions. However, in a subset of those, the robot was not able to complete the intervention due to HRI issues (the robot was not able to understand the user's answer) or due to issues while approaching the user (e.g., due to an obstacle that prevented the robot to reach a position close enough to the user). On average, the robot was able to perform interventions that (did not) required any answer from the user in 272 s (146 s).

These results are particularly relevant as they show that the proposed system was able to obtain stable performances during a long-term deployment of several months into cluttered environments as those reported in Fig. 4. Despite the difficulty of a long-term deployment in an uncontrolled and dynamic setting, robots, with the help of IoT sensors, were almost always able to identify the users (even under complex situations where users were moving across different rooms). The few failures when identifying the users were due to navigation or localization errors, or due to a failed search procedure.

6. Conclusions

In this paper, we presented a system that stems from the integration of an autonomous mobile robot with an IoT-based monitoring system to provide persistent monitoring, assistance, and stimulation to older adults living alone in their own houses within an AAL framework. The synergy between IoT and a Socially Assistive Robot was conceived to offer Long-Term Autonomy, performance, and reliability by bringing a strong added value to both the current SAR and IoT technologies. The experimental evaluation performed both in controlled settings and, most importantly, in 9 real-world apartments where the system was operating autonomously for 12 weeks each showed how the proposed framework could provide robust long-term monitoring and assistance to older adults living alone. Results show how the proposed system was able to increase availability, reliability, and quality of monitoring data collected by the IoT monitoring system, while also allow to detect and resolve anomalies and technical faults. The robustness and efficiency of SAR, thanks to the use of IoT-based data, allowed us to achieve long-term efficiency and autonomy in uncontrolled and changing environments.

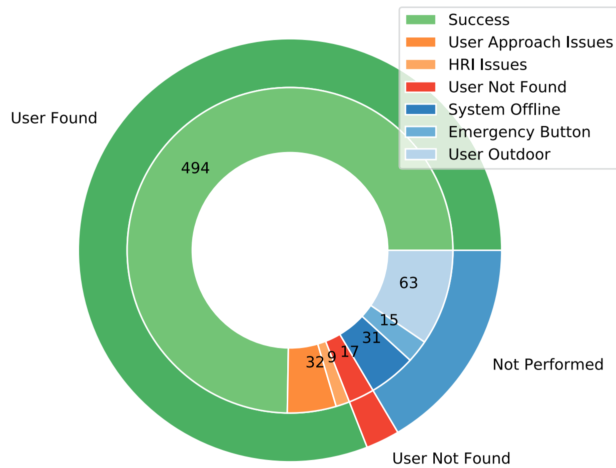


Fig. 11. Visualization of the performance of the robot in providing interventions to the user in real-world apartments during a time span of 12 weeks. The proposed system was able to identify the user inside the apartment in most of the cases (in green) and only in 17 cases the robot was not able to identify the user (red). Some interventions scheduled by the system were not performed as the user disabled the system or was detected as outdoor by the IoT sensors (blue). Full results are reported in Table 5.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgments

The work is partially supported by the European H2020 project MoveCare grant ICT-26-2016b– GA 732158 and by the PON project SI-ROBOTICS funded by the Italian government.

References

[1] H. Steg, H. Strese, C. Loroff, J. Hull, S. Schmidt, Europe is facing a demographic challenge ambient assisted living offers solutions, 2006, IST Project Report on Ambient Assisted Living.

[2] D.J. Cook, Health monitoring and assistance to support aging in place, J. UCS 12 (1) (2006) 15–29.

[3] P. Rashidi, A. Mihailidis, A survey on ambient-assisted living tools for older adults, IEEE J. Biomed. Health Inf. 17 (3) (2012) 579–590.

[4] D. Feil-Seifer, M.J. Mataric, Socially assistive robotics-ethical issues related to technology, IEEE Robot. Autom. Mag. 18 (1) (2011) 24.

[5] M. Pino, M. Boulay, F. Jouen, A.S. Rigaud, "Are we ready for robots that care for us?" attitudes and opinions of older adults toward socially assistive robots, Front. Aging Neurosci. 7 (2015) 141.

[6] K. Daniele, M. Marcucci, C. Cattaneo, N.A. Borghese, L. Zannini, How prefrail older people living alone perceive information and communications technology and what they would ask a robot for: Qualitative study, J. Med. Internet Res. 21 (8) (2019) e13228.

[7] M. Scopelliti, M.V. Giuliani, F. Fornara, Robots in a domestic setting: A psychological approach, Univers. Access Inf. Soc. 4 (2) (2005) 146–155.

[8] A. Dohr, R. Modre-Opsrian, M. Drobics, D. Hayn, G. Schreier, The internet of things for ambient assisted living, in: 2010 Seventh International Conference on Information Technology: New Generations, Ieee, 2010, pp. 804–809.

[9] S. Colantonio, G. Coppini, D. Giorgi, M.-A. Morales, M.A. Pascali, Computer vision for ambient assisted living: Monitoring systems for personalized healthcare and wellness that are robust in the real world and accepted by users, carers, and society, in: Computer Vision for Assistive Healthcare, Elsevier, 2018, pp. 147–182.

[10] L. Kunze, N. Hawes, T. Duckett, M. Hanheide, T. Krajník, Artificial intelligence for long-term robot autonomy: A survey, IEEE Robot. Autom. Lett. 3 (4) (2018) 4023–4030.

[11] O. Vermesan, A. Bröring, E. Tragos, M. Serrano, D. Bacciu, S. Chessa, C. Gallicchio, A. Micheli, M. Dragone, A. Saffiotti, et al., River Publishers, 2017.

[12] P. Simoens, M. Dragone, A. Saffiotti, The internet of robotic things: A review of concept, added value and applications, Int. J. Adv. Robot. Syst. 15 (1) (2018) 1729881418759424.

[13] L. Lammer, A. Huber, A. Weiss, M. Vincze, Mutual care: How older adults react when they should help their care robot, in: AISB2014: Proceedings of the 3rd International Symposium on New Frontiers in Human–Robot Interaction, Routledge London, UK, 2014, pp. 1–4.

[14] S. Rosenthal, J. Biswas, M. Veloso, An effective personal mobile robot agent through symbiotic human-robot interaction, in: Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems: Volume 1-Volume 1, International Foundation for Autonomous Agents and Multiagent Systems, 2010, pp. 915–922.

[15] F. Lunardini, M. Luperto, M. Romeo, J. Renoux, N. Basilico, A. Krpič, N.A. Borghese, S. Ferrante, The MOVECARE project: Home-based monitoring of frailty, in: 2019 IEEE EMBS International Conference on Biomedical & Health Informatics, BHI, IEEE, 2019, pp. 1–4.

[16] M. Luperto, M. Romeo, J. Monroy, J. Renoux, A. Vuono, F.-A. Moreno, J. Gonzalez-Jimenez, N. Basilico, N.A. Borghese, User feedback and remote supervision for assisted living with mobile robots: A field study in long-term autonomy, Robot. Auton. Syst. 155 (2022a) 104170.

[17] M. Luperto, J. Monroy, J. Renoux, F. Lunardini, N. Basilico, M. Bulgheroni, A. Cangelosi, M. Cesari, M. Cid, A. Ianes, J. Gonzalez-Jimenez, A. Kounoudes, D. Mari, V. Prisacariu, A. Savanovic, S. Ferrante, N.A. Borghese, Integrating social assistive robots, iot, virtual communities and smart objects to assist at-home independently living elders: The movecare project, Int. J. Soc. Robot. (2022b).

[18] J. Abdi, A. Al-Hindawi, T. Ng, M.P. Vizcaychipi, Scoping review on the use of socially assistive robot technology in elderly care, BMJ Open 8 (2) (2018).

[19] S.M. Rabbitt, A.E. Kazdin, B. Scassellati, Integrating socially assistive robotics into mental healthcare interventions: Applications and recommendations for expanded use, Clin. Psychol. Rev. 35 (2015) 35–46.

[20] D. McColl, W.G. Louie, G. Nejat, Brian 2.1: A socially assistive robot for the elderly and cognitively impaired, IEEE Robot. Autom. Mag. 20 (1) (2013) 74–83.

[21] M. Hanheide, D. Hebesberger, T. Krajnik, The when, where, and how: An adaptive robotic info-terminal for care home residents – a long-term study, in: Proceedings of ACM/IEEE Int. Conf. on Human-Robot Interaction, HRI 2017, 2017.

[22] L. Kunze, N. Hawes, T. Duckett, M. Hanheide, T. Krajnik, Artificial Intelligence for Long-Term Robot Autonomy: A Survey, IEEE Robot. Autom. Lett. 3 (4) (2018) 4023–4030.

[23] Á. García-Soler, D. Facal, U. Díaz-Orueta, L. Pigini, L. Blasi, R. Qiu, Inclusion of service robots in the daily lives of frail older users: A step-by-step definition procedure on users' requirements, Arch. Gerontol. Geriat. 74 (2018) 191–196.

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

[25] N. Hawes, C. Burbridge, F. Jovan, L. Kunze, B. Lacerda, L. Mudrova, J. Young, J. Wyatt, D. Hebesberger, T. Kortner, et al., The strands project: Long-term autonomy in everyday environments, IEEE Robot. Autom. Mag. 24 (3) (2017) 146–156.

[26] M. Broxvall, M. Gritti, A. Saffiotti, Beom-Su Seo, Young-Jo Cho, PEIS Ecology: Integrating robots into smart environments, in: Proceedings of the IEEE International Conference on Robotics and Automation, ICRA 2006, IEEE, 2006, pp. 212–218.

[27] R. Rasch, D. Sprute, A. Pörtner, S. Battermann, M. König, Tidy up my room: Multi-agent cooperation for service tasks in smart environments, J. Ambient Intell. Smart Environ. 11 (3) (2019) 261–275.

[28] S. Coradeschi, A. Cesta, G. Cortellessa, L. Coraci, C. Galindo, J. Gonzalez-Jimenez, L. Karlsson, A. Forsberg, F. S., F. Furfari, A. Loufti, et al., GiraffPlus: A system for monitoring activities and physiological parameters and promoting social interaction for elderly, in: Human-Computer Systems Interaction: Backgrounds and Applications 3, Springer, 2014, pp. 261–271.

[29] H.-M. Gross, C. Schroeter, S. Mueller, M. Volkhardt, E. Einhorn, A. Bley, T. Langner, M. Merten, C. Huijnen, H. van den Heuvel, A. van Berlo, Further progress towards a home robot companion for people with mild cognitive impairment, in: Proceedings of the IEEE Internationa Conference on Systems, Man, and Cybernetics, SMC 2012, 2012, pp. 637–644.

[30] H.-M. Gross, S. Mueller, C. Schroeter, M. Volkhardt, A. Scheidig, K. Debes, K. Richter, N. Doering, Robot companion for domestic health assistance: Implementation, test and case study under everyday conditions in private apartments, in: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2015, 2015, pp. 5992–5999.

[31] H.-M. Gross, A. Scheidig, S. Müller, B. Schütz, C. Fricke, S. Meyer, Living with a mobile companion robot in your own apartment-final implementation and results of a 20-weeks field study with 20 seniors, in: Proceedings of the IEEE International Conference on Robotics and Automation, ICRA 2019, IEEE, 2019, pp. 2253–2259.

[32] T. Wengefeld, B. Schuetz, G. Girdziunaite, A. Scheidig, H.-M. Gross, The morphia project: First results of a long-term user study in an elderly care scenario from robotic point of view, in: ISR Europe 2022; 54th International Symposium on Robotics, pp. 1–8.

[33] M. Bajones, D. Fischinger, A. Weiss, D. Wolf, M. Vincze, P. de la Puente, T. Körtner, M. Weninger, K. Papoutsakis, D. Michel, A. Qammaz, P. Panteleris, M. Foukarakis, I. Adami, D. Ioannidi, A. Leonidis, M. Antona, A. Argyros, P. Mayer, P. Panek, H. Eftring, S. Frennert, Hobbit: Providing Fall Detection and Prevention for the Elderly in the Real World, J. Robot. 2018 (2018) 1–20.

[34] D. Fischinger, P. Einramhof, K. Papoutsakis, W. Wohlkinger, P. Mayer, P. Panek, S. Hofmann, T. Koertner, A. Weiss, A. Argyros, M. Vincze, Hobbit, a care robot supporting independent living at home: First prototype and lessons learned, Robot. Auton. Syst. 75 (2016) 60–78, Assistance and Service Robotics in a Human Environment.

[35] M. Bajones, D. Fischinger, A. Weiss, et al., Results of field trials with a mobile service robot for older adults in 16 private households, J. Hum.-Robot. Interact. 9 (2019).

[36] L.A. Grieco, A. Rizzo, S. Colucci, S. Sicari, G. Piro, D. Di Paola, G. Boggia, IoT-aided robotics applications: Technological implications, target domains and open issues, Comput. Commun. 54 (2014) 32–47.

[37] C. Salatino, V. Gower, M. Ghrissi, A. Tapus, K. Wieczorowska-Tobis, A. Suwalska, P. Barattini, R. Rosso, G. Munaro, N. Bellotto, H. van den Heuvel, The enrichme project: A robotic solution for independence and active aging of elderly people with MCI, in: Proceedings of the 15th International Conference on Computers Helping People with Special Needs, Vol. 9758, 2016, pp. 326–334.

[38] S. Coşar, M. Fernandez-Carmona, R. Agrigoroaie, et al., Enrichme: Perception and interaction of an assistive robot for the elderly at home, Int. J. Soc. Robot. 12 (2020) 779–805.

[39] L. Fiorini, R. Esposito, M. Bonaccorsi, C. Petrazzuolo, F. Saponara, R. Giannantonio, G. De Petris, P. Dario, F. Cavallo, Enabling personalised medical support for chronic disease management through a hybrid robot-cloud approach, Auton. Robots 41 (5) (2017) 1263–1276.

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

[41] P. Rashidi, D.J. Cook, Keeping the resident in the loop: Adapting the smart home to the user, IEEE Trans. Syst. Man Cybern. A 39 (5) (2009) 949–959.

[42] A.M. Adami, M. Pavel, T.L. Hayes, C.M. Singer, Detection of movement in bed using unobtrusive load cell sensors, IEEE Trans. Inf. Technol. Biomed. 14 (2) (2009) 481–490.

[43] D. Riboni, C. Bettini, G. Civitarese, Z.H. Janjua, R. Helaoui, Fine-grained recognition of abnormal behaviors for early detection of mild cognitive impairment, in: 2015 IEEE International Conference on Pervasive Computing and Communications, PerCom, IEEE, 2015, pp. 149–154.

[44] P.N. Dawadi, D.J. Cook, M. Schmitter-Edgecombe, Automated cognitive health assessment from smart home-based behavior data, IEEE J. Biomed. Health Inf. 20 (4) (2015) 1188–1194.
[45] T. Tegou, I. Kalamaras, M. Tsipouras, N. Giannakeas, K. Votis, D. Tzovaras, A low-cost indoor activity monitoring system for detecting frailty in older adults, Sensors 19 (3) (2019) 452.
[46] A. Clegg, J. Young, S. Iliffe, M.O. Rikkert, K. Rockwood, Frailty in elderly people, Lancet 381 (9868) (2013) 752–762.
[47] L.P. Fried, C.M. Tangen, J. Walston, A.B. Newman, C. Hirsch, J. Gottdiener, T. Seeman, R. Tracy, W.J. Kop, G. Burke, et al., Frailty in older adults: Evidence for a phenotype, J. Gerontol. (A Biol. Sci. Med. Sci.) 56 (3) (2001) M146–M157.
[48] F. Lunardini, N.A. Borghese, L. Piccini, G. Bernardelli, M. Cesari, S. Ferrante, Validity and usability of a smart ball–driven serious game to monitor grip strength in independent elderlies, Health Inform. J. 1460458219895381.
[49] F. Lunardini, M. Malavolti, A.L.G. Pedrocchi, N.A. Borghese, S. Ferrante, A mobile app to transparently distinguish single-from dual-task walking for the ecological monitoring of age-related changes in daily-life gait, Gait Posture 86 (2021a) 27–32.
[50] F. Lunardini, D.D. Febbo, M. Malavolti, M. Cid, M. Serra, L. Piccini, A.L.G. Pedrocchi, N.A. Borghese, S. Ferrante, A smart ink pen for the ecological assessment of age-related changes in writing and tremor features, IEEE Trans. Instrum. Meas. 70 (2021b) 1–13.
[51] A. Cesta, S. Coradeschi, G. Cortellessa, J. Gonzalez, L. Tiberio, S. Von Rump, Enabling social interaction through embodiment in ExCITE, in: ForItAAL: Second Italian Forum on AAL, 2010, pp. 1–7.
[52] A. Orlandini, A. Kristoffersson, L. Almquist, P. Björkman, A. Cesta, G. Cortellessa, C. Galindo, J. Gonzalez-Jimenez, K. Gustafsson, A. Kiselev, A. Loufti, et al., ExCITE project: A review of forty-two months of robotic telepresence technology evolution, Presence (2017).
[53] F.-A. Moreno, J. Monroy, J.-R. Ruiz-Sarmiento, C. Galindo, J. Gonzalez-Jimenez, Automatic waypoint generation to improve robot navigation through narrow spaces, Sensors 20 (1) (2019) 240.
[54] J. Gonzalez-Jimenez, C. Galindo, J.R. Ruiz-Sarmiento, Technical improvements of the giraff telepresence robot based on users' evaluation, in: Proceedings of Thehe 21st IEEE Int. Symposium on Robot and Human Interactive Communication (RO-MAN 2012), 2012, pp. 827–832.
[55] M. Luperto, M. Romeo, F. Lunardini, N. Basilico, C. Abbate, R. Jones, A. Cangelosi, S. Ferrante, N.A. Borghese, Evaluating the acceptability of assistive robots for early detection of mild cognitive impairment, in: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2019, 2019, pp. 1257–1264.
[56] J. Renoux, M. Luperto, N. Basilico, M. Romeo, M. Millis, F. Lunardini, S. Ferrante, L. Amy, N.A. Borghese, A virtual caregiver for assisted daily living of pre-frail users, in: Proceedings of the 43rd German Conference on Artificial Intelligence (KI-2020), Lecture Notes in Computer Science book series (LNAI,volume 12325).
[57] A. Vuono, M. Luperto, J. Banfi, N. Basilico, N.A. Borghese, M. Sioutis, J. Renoux, A. Loufti, Seeking prevention of cognitive decline in elders via activity suggestion by a virtual caregiver, in: Proceedings of the 17th Int. Conf. on Autonomous Agents and MultiAgent Systems, AAMAS '18, 2018, pp. 1835–1837.
[58] F. Amigoni, V. Castelli, M. Luperto, Improving repeatability of experiments by automatic evaluation of SLAM algorithms, in: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2018, 2018, pp. 7237–7243.
[59] J. Wan, S. Tang, H. Yan, D. Li, S. Wang, A.V. Vasilakos, Cloud robotics: Current status and open issues, IEEE Access 4 (2016) 2797–2807.
[60] G. Hu, W.P. Tay, Y. Wen, Cloud robotics: Architecture, challenges and applications, IEEE Netw. 26 (3) (2012) 21–28.
[61] A. Deublein, B. Lugrin, (Expressive) social robot or tablet?–on the benefits of embodiment and non-verbal expressivity of the interface for a smart environment, in: International Conference on Persuasive Technology, Springer, 2020, pp. 85–97.
[62] B. Lewandowski, T. Wengefeld, T. Schmiedel, H.-M. Gross, I see you lying on the ground—Can I help you? Fast fallen person detection in 3D with a mobile robot, in: Proceedings of the 26th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN 2017, IEEE, 2017, pp. 74–80.
[63] M. Antonello, M. Carraro, M. Pierobon, E. Menegatti, Fast and robust detection of fallen people from a mobile robot, in: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2017, 2017, pp. 4159–4166.
[64] M. Garcia-Salguero, J. Monroy, A. Solano, J. Gonzalez-Jimenez, Socially acceptable approach to humans by a mobile robot, in: Applications of Intelligent Systems, 2019.

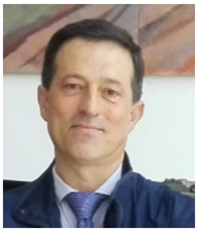
Matteo Luperto is an assistant professor the Dipartimento di Informatica Giovanni Degli Antoni at the Università degli Studi di Milano (Italy). He received his Ph.D. in Information Technology from the Politecnico di Milano (Italy) in 2017. In 2012 he participated and won with the Politecnico di Milano team the Virtual Robot Competition of the RoboCup Rescue Simulation League. His research interests are semantic mapping for autonomous mobile robots in indoor environments, with a particular attention on the analysis of the structural properties of buildings, and long-term autonomy for social assistive mobile robots and their application to e-health.

Javier Monroy is a postdoc researcher and assistant professor associated with the Machine Perception and Intelligent Robotics group (MAPIR) at the University of Málaga (Spain). He received his B.Sc (2007), and M.Sc (2010) in Electrical Engineering from this University. He joined the Department of "Ingenieria de Sistemas y Automatica" in 2009 and received his Ph.D. focusing on mobile robotics, in 2013. His research interest includes mobile robotics, perception systems, and machine learning. In these fields, he has (co)authored more than 20 JCR-ISI journals and 40 international conferences.

Francisco-Angel Moreno received his M.S. degree in Telecommunications Engineering and his Ph.D. in Mechatronic Engineering from the University of Malaga, Spain, in 2007 and 2015, respectively. He is author and coauthor of more than 20 journal papers and several communications in international conferences. He has also collaborated in different research projects within the MAPIR-UMA Group (MAchine Perception and Intelligent Robotics), regarding computer vision and mobile robot localization. He is currently an assistant professor at the University of Malaga.

Jennifer Renoux is a researcher at the Cognitive Robotic Systems Lab, Center for Applied Autonomous Sensor Systems, Örebro University (Sweden). She received her Ph.D. in Computer Science from the University of Caen Normandy (France) in 2015. Her research focuses on Human–Machine Teams and Artificial Social Intelligence, with special attention to adaptive communication planning, namely how to adapt artificial agents' communication to the human users' preferences, skills, and general situation.

Nicola Basilico received an M.Sc. degree in Computer Science and Engineering in 2007 and a Ph.D. in Information Technology in 2011 from Politecnico di Milano (Italy). He has been a postdoctoral scholar at the Robotics Laboratory at the University of California, Merced and worked as a research assistant at the Swiss AI lab IDSIA. From 2014 to 2019 he has been an assistant professor and from 2020 he is an associate professor at the Department of Computer Science of the University of Milan (Italy). His main research interests develop in the Artificial Intelligence area with a particular focus on Multi-Agent Systems and Autonomous Robotics.



Javier Gonzalez-Jimenez is the head of the Machine Perception and Intelligence Robotics (MAPIR) group (http://mapir.isa.uma.es) and full professor (Catedrático) at the University of Malaga. Javier received his B.S. degree in Electrical Engineering from the University of Sevilla in 1987. He joined the Department of ''Ingenieria de Sistemas y Automatica'' at the University of Malaga in 1988 and received his Ph.D. from this University in 1993. In 1991 he was at the Field Robotics Center, Robotics Institute, Carnegie Mellon University (USA) working on mobile robots as part of his Ph.D. Since 1996 he has been leading Spanish and European projects on mobile robotics and perception. His research interest includes mobile robot autonomous navigation, computer vision, and robotic olfaction. In these fields, he has co-authored more than 250 scientific works, including three books and about 100 SCI-JCR journal papers.

N. Alberto Borghese graduated with laude in 1986 in Electrical Engineering. He has been CNR researcher between 1987 and 2000, and then Associate and Full Professor at the Department of Computer Science of University of Milan where he leads the laboratory of Applied Intelligent Systems. His research activity is based on developing and testing on real problems methods and algorithms of computational intelligence, with particular attention to limited processing time. He has developed predictive models, based on hierarchical adaptive multi-scale approaches, adaptive clustering and statistical processing. More recently he has applied this knowledge to innovative platforms for e-Health and e-Welfare that integrate exergames, Artificial Intelligence, service robots, virtual communities and smart objects. He is coauthor of more than 80 journal papers (h index = 37), more than 140 refereed paper on conference proceedings, and holds 16 international patents. His research has been financed by industry and public bodies. He has been partner of projects Robocare (2001–2004) and SI-Robotics (2019–2022) financed by MIUR; coordinator of the following projects financed by the European Commission: FITREHAB (InterRegIVC, 2009–2011), REWIRE (FP7, 2011–2015) and MOVECARE (H2020, 2017–2019), and partner of the project ESSENCE (H2020, 2020–2022).