

Intuitive and Intelligent Solutions for Elderly Care



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1 Introduction

Vast demand for some particular, advanced and seamless solutions is spurring from current demographic realities, aging population, and burden of chronic diseases. Changing life-style related illnesses, increased demands of people for new, more sophisticated therapeutic and care methods are stretching the limits of innovations, specifically for the respected field considered in this article, the increase of symp-

This work was supported by a grant of the Romanian National Authority for Scientific Research and Innovation, the AAL Program with co-funding from the Horizon 2020 program projects “IONIS – Improving the quality of life of people with dementia and disabled persons” – AAL2017-AAL-2016-074-IONIS-1 and AAL-2016-074-IONIS-2 and – INCARE – Integrated Solution for Innovative Elderly Care”, project number AAL-2017-059-INCARE, by the Slovenia Ministry of Public Administration and by the subsidiary contract “CoRSAr” no. 1226/22.01.2018 for the grant 53/05.09.2016, ID 40270, cod MySMIS: 105976.

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toms and consequences related to older age, (like Alzheimer's disease, Dementia and Cognitive impairment). The European Commission in light of the challenge that also concerns stakeholders worldwide is encouraging many streams of endeavors. One of them being innovation in introducing solutions based on new models of services and state-of-the-art technology. Health services and home care services at a distance are the future for the aging population in many countries of the world. They present the possibility for building a sustainable health care system and contribution to a better life for older adults.

In this context, the current work is focusing on two Active and Assisted Living (AAL) projects which are developing information and communications technology (ICT) based platforms to support elderly persons and their caregivers. Both AAL IONIS [12] and AAL INCARE [11] projects originate from the very successful NITICS project [13, 17, 18]. In addition, contributions from the CoRSAr project (Platforma de Programare si Configurare a Robotilor Sociali si Asistivi) which is focusing on robotic based functionalities are also included in this research. IONIS exploits the innovation in NITICS and extends the platform with new technologies and upgraded services dedicated to persons suffering from mild cognitive impairment or incipient dementia and to their caregivers. It offers a fully integrated and validated solution at an affordable cost and with a high degree of personalization. IONIS is developed by exploiting location based services, sleep quality monitoring, communication services and the NITICS functionalities in order to offer continuous support at home (indoor area) and outside (outdoor area). A user-centered design involves extensive trials and piloting employed to both develop and validate the IONIS solution. The INCARE platform is extending NITICS with robotic features following a similar path as the CoRSAr project which can offer active support to the end-users, as exemplified further in this work. All presented projects implement functionalities specific for predictive (health, mobility and sleep patterns), preventive (medication compliance, hazard detection and enhanced activity) and personalized (e.g. robotic platforms).

2 Results and Discussions

2.1 End-User Involvement

A user-centered design was implemented in both IONIS and INCARE by involving elderly and caregivers during the whole development process. User input was also gathered in CoRSAr focusing on the perception of robotic platforms. Some important findings of the IONIS multinational survey and conjoint analysis are presented next.

A multinational survey The survey was carried out in four countries: Hungary, Poland, Romania and Slovenia. A total number of 121 primary (elderly) and 103 secondary (caregivers) users filled the dedicated questionnaires. The primary users

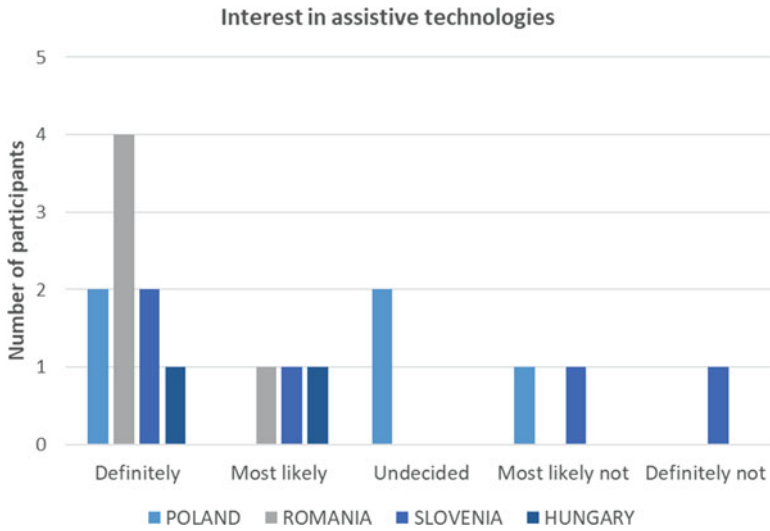


Fig. 1 Interest in using Assistive Technologies among the survey participants

were selected based on their score in the Mini-Mental State Examination (MMSE) test, the eligibility criterion being the presence of mild cognitive impairment or mild dementia signs (MMSE score 19–27 points).

The questionnaires focused on data useful for services design, implementation and testing, such as the living conditions, caregiving status and technology experience. Additional data covered the socialization activities of the primary users, their health status and acceptance [15] of the proposed IONIS services and their financial costs, memory impairment, sleep problems and independence in everyday tasks performed home and outdoors. The processed data was exploited in order to elaborate the Persona Cards and to generate reliable and realistic representations of potential elderly users. The survey results have shown that, although the primary users are generally not acquainted with the ICT solutions, the majority of them perceives the proposed services as useful (see Fig. 1). Most of the participants (70%) would definitely or most likely use Assistive Technology to help them in the activities of daily living. 15% of participants are not interested in Assistive Technologies and would most likely or definitely not use it. About 53% of included participants would definitely use Assistive Technology, 17.6% would most likely use it, about 16% of included participants would most likely or definitely not use it and 11.8% are undecided.

Conjoint analysis The goal of performing a conjoint analysis was to order the users’ preferences towards the IONIS functionalities and their possible implementation. A thorough conjoint user preference analysis was designed and implemented at this stage involving 61 total end-users (representing assisted persons and caregivers) from the same four end-user countries. Elderly and their informal caregivers expressed almost similar preferences, with a very small difference for the reminders

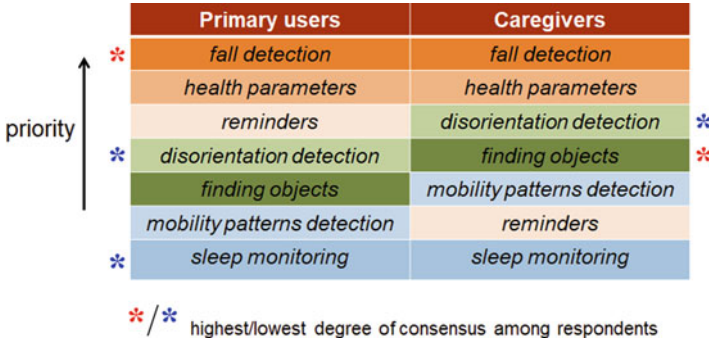


Fig. 2 End-user preferences for the identified services/functionalities

functionality. This scored much higher (3rd) for the elderly than for the caregivers (5th), trumping both the disorientation detection and finding objects (see Fig. 2). The main conclusion regarding the reminders functionality is that both the elderly and the caregivers appraised the email alternative as the least useful with almost the same levels of consensus. Also, both groups valued visual messages with approximately the same ‘strength’, but the persons in need found the voice messages as being the most useful.

2.2 Novel ICT Approaches in IONIS and INCARE

Both IONIS and INCARE projects follow an intelligent and innovative approach regarding the technologies considered in their integration. Particularly, INCARE aims to integrate robotic platforms as service robots. Additionally, distributed AI approaches are considered for privacy compliance purposes. In this section, we present an overview the end-user needs identified in elderly-robot interaction experiments, a laboratory environment example to be tested within INCARE and recent trends in federated learning.

Elderly-robot interaction For a successful integration in elderly care environments, robots must be carefully designed such that their appearance and functionality match the needs and expectations of both elderly and caregivers [8, 16]. The human necessities and reception of robots within an elderly care environment are usually identified through the use of questionnaires, focus groups and live sessions. The quality evaluation of human-robot interaction in the context of elderly care is focused on the quality of life impact for the caregivers and caretakers [8], but also on psychological and behavioral effects on the elderly, such as decreases in their level of stress and loneliness and improvements in their predisposition to engage in communication activities and overall mood [4]. A review on the robot acceptance identifies age, gender, experience with technology and cultural background as human factors, while appearance, human resemblance and dimensions, gender and

personality are the robot characteristics of high importance [3]. Concern is also directed towards personal data confidentiality and the assessment of the risks and benefits [1]. According to multiple studies, robots resembling human beings usually receive a negative feedback, the robots with a more machine-like appearance being preferred [1, 3, 16, 24].

In general, the preexisting attitudes towards robots proved to be a major factor in their acceptance [20]. In [2], the previous perception of robots and the quality of experience in a setup examining the feelings of the patients during blood pressure and heart rate readings performed by a robot assistant and by a medical student showed a high correlation. The patients were able to identify multiple benefits of the healthcare robots, such as workload balancing for the caregivers, daily routine scheduling and compensating for staff shortages, indicating that low human comfort around robots due to lack of exposure might be a principal negative factor in their acceptance. Several areas of improvement for elderly-robot interaction include empathy emulation, behavior adaptability [21] and unpredictability, as the capacity to generate actions that are not necessarily reactions to user input [10].

Scenario in laboratory environment Various scenarios are intended to be tested within INCARE and CoRSAr, where a robot interacts with elderly and their formal and informal caregivers. The development of cloud services [6] and map creation methods [22] substantially support the effectiveness of not only robot navigation, but also both speech recognition and speech synthesis. Hence, this type of communication was chosen for being both effective and intuitive.

The first scenario covers the need for delivery of small items (e.g. drinks) ordered by the elderly, where the robot substitutes the staff of e.g. elderly facility and the staff can concentrate on more complicated activities. It is assumed that the older person stays in one room, while the staff operates in the other room – i.e. kitchen. The robot will perform its delivery task while also detecting hazards [5, 7] and informing about them. The robot considered for the scenarios is the TIAGo [14, 23] by PAL robotics. The scenario consists of the following, subsequent steps: (1) An elderly person calls for a robot; (2) The robot approaches the elderly person; (3) The robot asks for orders; (4) The elderly person requests for a drink, e.g. tea; (5) The robot confirms an order; (6) The robot goes to the kitchen; (7) The robot approaches the staff in the kitchen and asks for the particular drink to be put on it; (8) The staff confirms that the delivery is ready and placed on the robot; (9) The robot informs that it starts to go back to deliver the order; (10) The robot approaches the elderly person and informs that it has the delivery; (11) The robot asks the elderly person to take the drink; (12) The older person takes the drink and confirms the action.

Federated learning in AI In the past few years, machine learning has led to major breakthroughs in various areas, such as computer vision. Much of this success has been based on collecting huge amounts of data. Machine learning applications need to collect data that are privacy-invasive.

Federated Learning is a distributed form of machine learning approach where the training process is distributed among many users using a training data set composed of decentralized data. A server has the role of coordinating everything and most of the work is performed by each device. Steps involved in the federated learning

are: (1) the server initializes the model and each device/client downloads the global model; (2) the model is updated using its own data; (3) each personalised trained model is sent to the server; (4) on the server a federated average function is used to generate a much improved version of the model than the previous one; and (5) the improved version is sent to all the devices.

Federated learning looks similar with distributed machine learning on a technical level. But there are some major differences: (1) huge number of clients; (2) learning data for each user is obtained from different distribution – two similar users might have similar training data, but two randomly users can obtain totally different data; (3) unbalanced number of examples per device and (4) slow and unstable communication.

In 2018, Intel began a collaboration with the Center for Biomedical Image Computing and Analytics at the University of Pennsylvania showing the first proof concept for federated learning applied for real medical images used for semantic segmentation of brain tumors from images. The study demonstrated training of a convolutional neural network (U-Net model) using federated learning with an accuracy of 99% as the same model trained with the traditional methods [19]. Paper [9] uses electronic medical records together with federated learning to predict disease incidence, patient response to treatment, and other healthcare events. A community-based federated machine learning method was proposed. The method clusters patients into similar clinically communities that has similar diagnoses and geographical locations, learning one model for each community. Also, the learning process keeps data locally at hospitals. Evaluation was performed on 50 hospitals, each with 560 patients. Results show that the proposed method outperforms the baseline federated machine learning method.

3 Conclusions

Many professional teams, companies, policy makers and individuals are working in the field of the challenges posed by AAL. All efforts are necessary to make worthwhile changes providing technological and procedural solutions and to bring them closer to the end-users. Understanding their needs and experiences and enhancing the acceptance of solutions being developed are crucial to make AAL solutions widely and fairly available and bring about significant structural change. For this purpose, the presented projects offer predictive, preventive and personalized support through their design and implemented functionalities.

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