



A critical analysis of an IoT–aware AAL system for elderly monitoring

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HIGHLIGHTS

- Unobtrusive systems are useful for monitoring elderly behaviour and detect changes.
- Wearable devices for BLE indoor positioning and body motility are energy greedy.
- Digest mode for data sending to the Shared Repository is the most preferable way.
- Linked Open Data to share results is fundamental in a Smart City perspective.
- Frailty/MCI risk detection based on high-level geriatric (sub-)factors is effective.

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ABSTRACT

A growing number of elderly people (65+ years old) are affected by particular conditions, such as Mild Cognitive Impairment (MCI) and frailty, which are characterized by a gradual cognitive and physical decline. Early symptoms may spread across years and often they are noticed only at late stages, when the outcomes remain irrevocable and require costly intervention plans. Therefore, the clinical utility of early detecting these conditions is of substantial importance in order to avoid hospitalization and lessen the socio-economic costs of caring, while it may also significantly improve elderly people's quality of life. This work deals with a critical performance analysis of an Internet of Things aware Ambient Assisted Living (AAL) system for elderly monitoring. The analysis is focused on three main system components: (i) the City-wide data capturing layer, (ii) the Cloud-based centralized data management repository, and (iii) the risk analysis and prediction module. Each module can provide different operating modes, therefore the critical analysis aims at defining which are the best solutions according to context's needs. The proposed system architecture is used by the H2020 City4Age project to support geriatricians for the early detection of MCI and frailty conditions.

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1. Introduction

Low birth rates and higher life expectancy are transforming the composition of world population, with a marked transition towards a much older population structure, a development already apparent, for example, in several EU Member States. The population of the EU-28 on 1 January 2017 was estimated at 511.5 million, with a percentage of elderly people (aged 65 or over) of 19.4%, showing an increase of 0.2 percentage points compared with the previous year and an increase of 2.4 percentage points

compared with 10 years earlier. Another aspect of population aging is the progressive aging of the older population itself, as the relative importance of the very old is growing at a faster pace than any other age segment of the EU's population. As a result, the share of older people in the total population will increase significantly in the coming decades, as a greater proportion of the post-war baby-boom generation reaches retirement. The share of those aged 80 years or above in the EU-28's population is projected to more than double between 2017 and 2080, from 5.5% to 12.7%.¹ Similar conditions are typical of main industrialized nations, like USA, China and Japan, where the percentage of aging population is expected to rapidly grow (up to 37.70% in

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¹ http://ec.europa.eu/eurostat/statistics-explained/index.php/Population_structure_and_ageing.

2050 in Japan²), despite, in some cases, a population decrease is forecasted (like in Japan).

Aging processes result in some degree of decline in cognitive capacity, usually including the following symptoms: forgetfulness, decreased ability to maintain focus, decreased problem solving capacity. If left unchecked, these symptoms often progress into more serious conditions, such as dementia and depression, or even Alzheimer's disease (AD).³ Mild Cognitive Impairment (MCI) is a condition in which people face memory problems more often than that of the average person their age. These symptoms, however, do not prevent them from carrying out normal activities and are not as severe as the symptoms for Alzheimer's disease. Symptoms often include misplacing items, forgetting events or appointments, and having trouble finding words [1]. According to recent research, MCI is seen as the transitional state between cognitive changes of normal aging and Alzheimer's disease.⁴

If these warning signs are not timely caught and turn out into more severe diseases, then this will imply a significant decrease in the quality of life for both elderly people and their relatives, but it also creates a burden for national health services, which must face an evolving scenario for interventions. Given that the demand for health care rises with age, countries with rapidly aging populations must allocate more money and resources to their health care systems. With health care spending as a share of Gross Domestic Product (GDP) already high in most advanced economies, it is difficult to increase spending while ensuring high quality services in the case of publicly funded or government-administered health care systems.⁵ Additionally, the health care sector in many advanced economies faces common issues, including labour and skills shortages, increased demand for long-term home-care systems and the need to invest in new technologies. All of these cost escalators make it more difficult for existing systems to handle the increased prevalence of age-related chronic diseases, therefore, in a very near future, aging population is going to become an economic concern for all the citizens and one of the greatest social and economic challenges for world societies in the 21st century.

Recently, Information and Communication Technologies (ICTs), in particular Internet of Things (IoT)-enabling technologies [2] and devices, like smart-objects, connected sensors and actuators, wearable sensors, mobile devices and so on, have allowed the setup of the so-called Ambient Assisted Living (AAL) systems [3], which can be seen as the application of ICTs in a person's (especially an elder person) daily living and working environment, in order to enable him/her to stay active longer, remain socially connected and live independently into old age. Moreover, in the very last years, the AAL approach is moving towards a City-wide approach, considering the elderly people not just as subjects with special needs, but as individuals being part of a community, having own relational networks made up of relatives, friends and formal/informal caregivers, and carrying out even complex activities, both in a home and in a city context. This has been made possible also by the recent advent of Big Data Management and Analysis platform and tools [4], allowing the storage, management, analysis and visualization of data collected from unobtrusive sensors deployed at person, home and city level, and characterized by high volume, velocity and variety. All collected data are analysed with the aim of defining the behavioural profile

of each elderly person, in order to early detect any potential risk related to Frailty and Mild Cognitive Impairments (MCI) and to timely intervene.

In this context, this article extends the work presented in [5], which focused on a performance analysis of the first three main building blocks of an IoT-aware elderly monitoring system, i.e. the data capturing layer in home and in city environments, the Cloud data store and management layer and, the data analytics for risk related to MCI and frailty detection layer. The first block deals with the collection, through unobtrusive technologies and devices, of data related to elderly's behaviour during their daily activities, both in indoor and outdoor environments. The second block is in charge of storing, semantically enriching, managing and providing all the collected data, in order to make them available for further processing. Finally, the last block applies novel risk detection algorithms on the gathered data in order to define the risk related to MCI and frailty profile of each individual.

This system architecture (hardware and software modules, tests, analysis, etc.) has been designed, developed and analysed by all co-authors in the frame of the H2020-funded City4Age project to help geriatricians in identifying the onset of MCI and frailty conditions in elderly people. This paper represents the result of authors' work in the last three years within the project and it aims to collect in a single document all the descriptions of the main building blocks. Moreover, a first step of performance evaluation is also presented (with several experimental results obtained through different test campaigns, both in controlled test environment and in pilot sites), together with some lessons learnt analysis. In particular, this work provides a detailed description of the above-mentioned system architecture components and an updated performance analysis of each module, whose results are used to drive a discussion about limitations of the current system and suggestions on how to overcome them. The main concerns are related to the potentially huge amount of data generated and handled by the system, which does not have real-time constraints, and therefore it can adopt intermediate buffers, batch communications and asynchronous elaborations without affecting performance. Currently, the actual users of the system are quite limited, since they refer to highly specialized profiles, such as geriatricians, domain experts, researchers, policy makers and so on, who have access to aggregated and coarse-grained data. However, computational times must be kept in a reasonable range in order not to affect user experience, especially during the data visualization and analysis phases.

The article is structured as follows. In Section 2 a brief overview of similar works in the field of IoT-aware AAL and elderly monitoring systems is presented, along with a critical analysis with respect to the approach proposed by the City4Age project. In Section 3, an overview of the City4Age project is briefly presented, which fosters reader's comprehension of the technical details of the Personal Data Capturing System (PDCS), the Shared Repository (SR), and the Risk Analysis Model and Dashboard, deeply described in Section 4. Section 5 deals with the performance analysis of these three components, while a critical discussion about obtained results is carried out in Section 6. Finally, in Section 7 the conclusions and future developments of the work are drawn.

2. State of the art and related work

The concept of "Smart Cities" appears in the literature as a sensing and intelligent city capable of providing different services based on citizens' demands by using their data collected through different sources. The gathered data are used by the so called "sensor consumers" i.e. researchers, companies and governments, to create innovative solutions to foster the citizens'

² <https://www.caixinglobal.com/2018-07-20/chart-chinas-aging-population-101306922.html>.

³ <http://www.lifeextension.com/Protocols/Neurological/Age-Related-Cognitive-Decline/Page-01>.

⁴ <https://www.ncbi.nlm.nih.gov/pubmed/14732621>.

⁵ <https://www.investopedia.com/articles/investing/011216/4-global-economic-issues-aging-population.asp>.

well-being [6]. In fact, the “smart” concept of a city is only the final step of a complex process in which different innovative solutions and technologies are involved. One of them is the Internet of Things (IoT). IoT covers the necessity of having different ways of obtaining data from different sources, in an obtrusive or unobtrusive manner, by using a set of different common daily devices. These devices have the advantage of being connected to the Internet to send real information from their usage. Some examples of data gathered by these devices are temperature measures, presence of person in an environment, usage of different devices (coffee machines, TVs, doors...) and so on. With the inclusion of the IoT paradigm as a method to acquire data, several authors have been able to present different approaches with the aim of using these sensing devices to collect data and exploit them in a city-wide context. For example, in [7], authors outline the challenges of using IoT devices inside a city to create the so called “Smart Cities”. They review several architectures to acquire data from different IoT based sensors and describe what are the different purposes to be covered in order to acquire useful data. In addition, authors describe a project called “Padova Smart City”, to show a real example of an architecture which is capable to obtain data in a real scenario. Authors in [8], present the current technical IoT architecture needed to deal with the necessities of having a connected system thought IoT devices. They describe the basic requirements to implement an IoT based architecture in a smart environment and describe different key challenges to improve it, e.g. the necessity of improving privacy, a standardization of the software used by devices, an improvement of data confidentiality, encrypted connections, improved network security and so on. Other authors have similar ideas and present approaches in which they describe what is the most suitable architecture to use IoT devices to create “Smart Cities”, like authors in [9]. These researchers present a Cloud Centric Vision in which they comprise the architecture needed to connect IoT based devices to a Cloud server. They present different architectures and discuss the importance of having different requirements for data ownership, security and privacy. Moreover, authors present a roadmap of the key technological developments in the context of IoT that would impact in the future.

Not only the design of the suitable architecture is needed to use IoT devices in a city-wide context, but also, it is important to apply these architectures to improve the well-being of the citizens. For that reason, authors have been presented different implementations to use IoT devices inside a “Smart City”, for example, in the health research field. In [10], authors present a review of a set of different contributions to demonstrate the importance of the IoT devices in the medical domain. They show examples of how data can be integrated in a city by using IoT devices and Fog computing, putting a special emphasis into the possibility of being used by telemedicine to avoid medical costs in the future. In addition, they present the *eHealth* protocol stack: an IoT and Fog computing-based architecture to acquire data from a user to provide medical services and an accurate information about their health status. To do that, they present a set of different devices which can be attached to the human body in order to track its medical conditions. In addition, authors describe what are the needed requirements to build a solid IoT based infrastructure and how to exploit the acquired medical data. Other authors, like [11], present a brief description of the importance of using IoT based devices to create “Smart Cities” and the importance of using these technologies to create a healthy city to improve the citizens' health.

These contributions pave the way in which the IoT based devices can play a pivotal role in order to obtain data from citizens to provide different services and solutions. However, there is a group of citizens which needs further attention and these

solutions can be beneficial in order to improve their well-being. This group is the elderly citizens.

The aging of urban population has resulted in an increase of the research in the area. The necessity of knowing how to integrate this portion of the population in the city is introducing new ways of communication between citizens and the city. Several projects have developed different solutions to address this topic, trying to expand ambient assisted environments from indoor spaces to outdoor and public environments, aiming to create different services to improve the well-being of the citizens, with attention to the elderly citizens' needs. In general, these projects gather data from citizens, store them securely and analyse them to create an intervention-based system that can be used in general or specific scenarios. These interventions can address potential risk cases of degenerative diseases like MCI or frailty and can inform geriatricians, caregivers or authorized persons to help them.

PreventIT [12] is a system that uses smartphones and wristbands to collect users' data and identify possible risk factors based on their behaviour. The users' data are gathered both indoor and outdoor and, based on these data, an intervention system detects if the user has a health risk and needs an intervention from external partners like geriatricians or caregivers. This solution can be deployed in a city-wide context since the system is scalable.

FrailSafe [13] combines medical and technological objectives to create a complete system that covers various objectives: (i) understanding the frailty of elderly citizens; (ii) use the obtained data to infer future outcomes; (iii) develop different tools to be used to assist the citizens; (iv) create recommendation services to prevent risky conditions. This project gathers individual data for each user both indoor and outdoor using different data sources such as GPS systems, movement sensors or smartphones. Data are used to enrich the intervention system and make it more accurate. However, this project is only focused in the individual monitoring and intervention system; hence it is not prepared to be used in a city-wide context because the adopted architecture is not designed for large scale volume of data.

The Netstore [14] project aims to develop an innovative multi-dimensional, personalized coaching system to support healthy aging. This system supports elderly citizens by giving them hints and suggestions for a healthy lifestyle based on the data acquired from their daily activities. This project uses ICT based solutions to extract user data from indoor and outdoor spaces and can be scalable in a city-wide context to cover all citizens of a big city. Using the acquired data, the project builds a virtual personalized coach, which gives advice to improve the citizens well-being.

AGNES [15] uses ICT based solutions to extract data from users in indoor spaces. The main idea of this approach is to create a web-based social network to stimulate elderly citizens and promote healthy behaviours. This web-based system provides information about the health conditions of the monitored users. The project gathers information about the users and shows it in an easy way to be interpreted by informal careers, friends and family members. The data obtained are shared over the Web to have a remote access point; however, the project does not gather data from outdoor spaces and it is not prepared to be used in a city-wide context, because the architecture is focused on obtaining data from indoor spaces without giving a scalability process.

STIMULATE [16] presents an interesting approach based on ICT tools to gather information about elderly citizens and make suggestions about what is the best itinerary to take when they need to move around the city. These itineraries are based on the users' capabilities and consider their physical conditions. The platform uses a mobile device to help the users in their travels. The project only considers outdoor spaces. This project does not

gather data from indoor spaces and it is not prepared to be used in a city-wide context because the project is designed to be used only by few users.

eWALL [17] is a project that uses a “smart wall”. This wall provides information about the health status of the monitored user, giving information in real time about his/her clinical measures such as cardiopulmonary conditions or neuromuscular movements. The main objective is to promote the independent living of elderly citizens by gathering information about their health status in an indoor environment. This approach only gathers data from indoor spaces, and it is prepared to be scalable in a city-wide context. However, this project does not gather data from outdoor spaces; nor it considers needs and performances of the elderly citizens when they perform outdoor activities.

USEFIL [18] is a project which contains some similarities with inCASA project [19] but using only open-source based solutions. The project objective is to gather data from elderly citizens in their home environment by using only low-cost IoT based solutions. Gathered data are used to build a personalized profile that will receive alerts about how they can improve their lives to foster an indented living. This approach is focused mainly on acquiring data from indoor spaces rather than outdoor spaces. In addition, the project is not designed to be scalable in a city-wide context.

CARE [20] creates automatic alarms based on the gathered data from indoor monitoring. These alarms are used when the system detects potential critical situations such as falls or health risks. The main objective of this project is to create an intelligent environment to detect critical situations related to elderly citizen. This project only uses stationary technologies, so it is not designed to gather data from wearables, smartphones or any type of devices that can record data from the user when he/she is not in the augmented environment. The project can be scalable to be used in a city-wide context but limited only to indoor spaces.

The projects discussed so far do not share data through a Linked Open Data approach, to give a semantic meaning to all gathered and processed data in order to allow their access from third parties. These data can be an invaluable source of knowledge to improve the current systems or to create new ones. The following projects make use of the Linked Open Data approach.

Smart Santander [21] is a city-wide based project. This project tries to improve Santander citizens' well-being by gathering data in an unobtrusive manner. The project gathers data from citizens in indoor and outdoor spaces by using a set of different ICTs solutions, such as movement sensors, NFC, GPS or QR codes. In addition, this project contains a module that can transform the acquired data into semantic data to be shared to third parties and try to develop new solutions that can improve the Santander's citizens life.

The Smart Odense [22] project is an initiative of the Municipality of Odense and the University of Southern Denmark with the aim of improving the Odense citizens' lives. This project deploys different sensors in the city to monitor the citizens activities, for example if a citizen uses the bike service the sensors will record its usage in real time and will inform to the potential users about where free parking lots for bicycles are. In addition, the project tracks the most vulnerable citizens to know if they need interventions and control the indicators that detect if they are at risk being excluded from the community. This project contains similarities with Smart Santander but only gathers data from outdoor spaces.

ACTIVAGE [23] project presents an open framework for providing semantic interoperability of IoT platforms for active and healthy aging. The project provides a set of different layers based on IoT solutions to gather data from citizens and share it to third parties by using the Linked Open Data principles. The core idea

of the project is to create an intelligent environment to mitigate the frailty conditions and preserve the elderly citizens' quality of life by giving them a way to be self-independent.

The common feature of all these projects is the lack of a rule engine-based reasoner, which can create new statements in order to improve the meaning of the semantic data by using a set of rules. A comparison among these projects is presented in Table 1, which also outlines the differences with the City4Age project, described in the following Section 3. The first two columns, titled *Indoor* and *Outdoor*, depict the capability of the system to gather data from indoor or outdoor spaces (a house is considered an indoor space and a park is considered an outdoor space). The *City-Wide* column depicts if the system covers city-wide demands or is designed for a single location. The column *Linked Data Support* illustrates if the solution follows the Linked Open Data approach to share semantic data over the web. The last column, called *Reasoning Support*, illustrates if the system can perform a reasoning process to create new statements based on a set of elicitation rules.

The presented approaches contain different features that cover tailored situations, which make them useable under specific conditions. However, they do not cover all features that the City4Age project approach covers, as indicated in the last row in Table 1 and as it will be clearer after reading Section 3, because none of them can provide a solution to gather data from different sources, to store them securely, to give ability to select what data will be semantically shared, to infer new knowledge by using a set of rules and finally to provide a tool to share the data using a semantic approach.

The architecture proposed in this article provides a tool for gathering data from different IoT middlewares, for storing them in a persistent combined relational/binary-JSON data store in order to, lately, convert them into semantic data and share them using a SPARQL [24] based endpoint. This approach tries to expand and share the gathered data using a reasoning process with a set of elicitation rules that infers the converted semantic data and creates new knowledge to be shared to third parties. Data are converted into semantic data from a relational database when third parties request the stored data. This solution is more scalable and can process large volumes of data. In addition, this allows defining what is the information that will be converted into semantic data, making the selection of the desired data and sharing it semantically over the web. Therefore, with this solution data are acquired by different sources of IoT-based deployments (in the context of a Smart City) and stored in a secured silo; then, a set of different tools to exploit these data are provided, such as analytical dashboards, big data analysis, or advanced intervention systems. Moreover, a semantic annotation and inferring phase, both on original and processed data, can be performed, in order to extract further knowledge. Data sharing, through the use of a SPARQL based endpoint, makes them available to be exploited by governments, researchers or companies to create a gate through which they can access the stored data and create new business opportunities, research innovations or social improvements.

3. City4Age project description

City4Age [25,26] is a Horizon2020-funded research and innovation project with the goal of enabling age-friendly cities, aiming at the creation of an innovative framework based on ICT tools and services that can be deployed and used by European cities to enhance the early detection of risk related to frailty and MCI. It provides also a wide range of personalized interventions that can help the elderly population to improve their daily life by promoting positive behaviour changes. The project includes six pilot sites to test the outcomes of the research, which are located in Athens

Table 1
Comparison of related work projects.

Project name	Indoor	Outdoor	City-wide	Linked Data Support	Reasoning support
PreventIT	Yes	Yes	Yes	No	No
FrailSafe	Yes	Yes	No	No	No
Nestore	Yes	Yes	Yes	No	No
AGNES	Yes	No	No	No	No
STIMULATE	No	Yes	Yes	No	No
eWALL	Yes	No	Yes	No	No
inCASA	Yes	No	No	No	No
USEFIL	Yes	No	No	No	No
CARE	Yes	No	Yes	No	No
S. Santander	Yes	Yes	Yes	Yes	No
S. Odense	No	Yes	Yes	Yes	No
ACTIVAGE	Yes	Yes	Yes	Yes	No
City4ge	Yes	Yes	Yes	Yes	Yes

(GR), Lecce (IT), Birmingham (UK), Madrid (ES), Montpellier (FR) and Singapore. Fig. 1 shows the City4Age logical architecture [27], where the leftmost part deals with the unobtrusive detection of elderly behaviour patterns during their everyday life, in indoor and outdoor environments, also at a city-wide scope. Collected data are then stored and managed in a central repository, which acts as a data source for novel behavioural analysis and risk detection algorithms (the rightmost block). This step produces a list of possible customized interventions for each subject, which can be directly administered to the elderly, or after the evaluation by a multidimensional assessment team. The smartphone plays a central role in this architecture, acting in many cases as a gateway for data transmission and as a terminal for interventions.

In the context of the City4Age risk modelling, a set of Geriatric Factors (GEFs) and Geriatric Sub-Factors (GESs) have been defined as quantitative indicators of the MCI and frailty risk associated to an elderly person [28]. These indicators derive from the most commonly used tools in current geriatrics practice, that measure MCI and frailty based on behaviour and human activities monitoring. A partial list of the defined GEFs and GESs is shown in Table 2.

The numerical values of GEFs and GESs result from the aggregation of data with a lower level of abstraction and a larger basin of sources. Therefore, in order to address issues related to heterogeneous data sources, low level technologies, semantic interpretation and so on, the City4Age project has defined the notion of Low-level Elementary Actions (LEAs). A LEA is the finest grain atomic information used to detect behaviour of elderly people. It is a structured data object that relates to start/stop events of user basic actions and contains additional information about time and position of the action that is being taken.

LEAs are grouped in macro-categories according to their scope, such as (i) **Person LEAs** – for tracking user states about motility, like standing, moving, walking, etc., but also for collecting data about the usage of smartphone for calling and the number of visits paid or received – (ii) **Home LEAs** – for tracking user positions inside his/her home environment; for collecting data about the usage of home appliances and furniture, like fridge, TV, washing machines, cabinets, etc. – (iii) **City LEAs** – for tracking user positions, both inside monitored places in the city being part of the City4Age pilot scenarios (shops, offices, pharmacies, etc.) and in outdoor spaces in the city (streets, parks, etc.); for tracking the interaction of user with public transportation systems.

LEAs are collected as soon as they happen and sent asynchronously to the central repository for further elaboration. Since a large number of LEAs occurrences can be generated during the day, the City4Age project has introduced the concept of Measure as a daily indicator that synthesizes a set of occurrences of a given LEA. For example, by analysing all LEAs related to the entering and exiting of the user in a room (such as the bathroom), it can be computed how many times the user went to bathroom in a day

and the average time of permanence. These are typical examples of Measures, generated on a daily basis, that make sense from a geriatric point of view to assess changes of behaviour relevant for MCI/Frailty. Starting from these and other daily Measures, GEFs and GESs indicators can be computed in order to define a risk profile of each elderly person on a monthly basis. A well-defined and shared vocabulary of LEAs and Measures labels has also been defined as a deliverable of the project, with the aim of providing a common language for all low-level data producers.

In order to abstract low-level details without losing information during the data acquisition process, the concept of Common Data Format (CDF) has been introduced with the aim to define a data object which is used to exchange data and information with a uniform and shared meaning, hiding all technological low-level details. In this way, data gathered by different devices, can be treated in the same manner, avoiding concepts misalignment and loss of knowledge. The CDF, along with the shared vocabulary of LEAs and Measures labels, provides a first level of abstraction with respect to raw data generated from sensors. There exist two different CDFs, shown in Tables 3 and 4, used to transmit LEAs and Measures to the City4Age Shared Repository.

4. Description of system architecture

This work defines a general architecture for unobtrusively collecting data coming from a heterogeneous sensing infrastructure. In particular, this work is focused on the first three layers of the proposed solution, the so-called Personal Data Capturing System (PDCS), the Shared Repository (SR) and the Risk Analysis Model and Monitoring Dashboards (RAMMD), shown in Fig. 2 [29].

The main task of the Personal Data Capturing System is to collect raw data from heterogeneous sensors deployed in physical environments (independently of both their specific technologies and communication protocols) and process them to calculate LEAs and Measures to be sent to the Shared Repository. The PDCS is internally composed of two main logical blocks. The Local Environment Building Block (LEBB) provides a modular set of software components (generally installed on smartphones or embedded devices acting as gateways), which allows the communication with different sensing technologies according to the respective standards and protocols in a uniform way. This capability abstracts the heterogeneity of the physical devices and provides a high degree of expandability to include upcoming technologies. The LEBB core logic translates raw data into LEAs and sends them, through a well-defined REST APIs, to the Cloud Building Block (CBB). It is in charge of performing further computations in order to calculate Measures based on the given LEAs. Finally, the CBB is in charge of sending both LEAs and Measures to the SR.

The Shared Repository integrates the data received from the IoT infrastructure and provides a semantic meaning to those data following the Linked Open Data paradigm. This process also

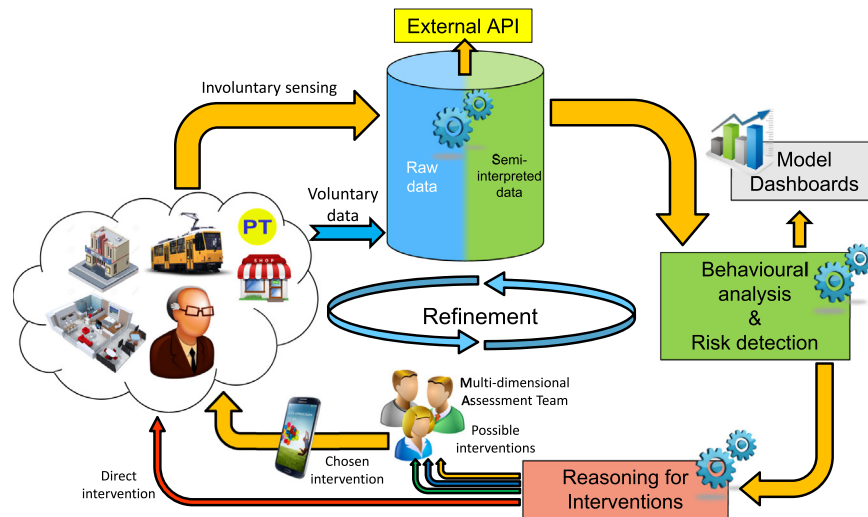


Fig. 1. System architecture of the City4Age project. It collects elderly's behavioural data through unobtrusive technologies and store them in a central shared repository, so that risk detection algorithms can be applied on them to produce customized interventions.

Table 2
Excerpt of GEFs and GESs list.

Geriatric factors	Geriatric sub-factors
Motility	Walking, climbing stairs, still/moving, moving across rooms
Basic activities of daily living	Bathing and showering, dressing, self-feeding, going out
Instrumental activities of daily living	Ability to cook food, housekeeping, laundry, phone usage, new media communication, shopping, transportation
Socialization	Paying/receiving visits, attending senior centres, attending other social places
Cultural engagement	Visiting cultural or entertainment places, watching TV, reading
Environment	Quality of housing, quality of neighbourhood
Health – Physical	Falls, weight, weakness, pain, appetite, exhaustion, quality of sleep, visits to doctors, visit to health related places
Health – Cognitive	Abstraction, attention, memory, mood

Table 3
LEA Common Data Format (CDF).

Property	Description
<i>action</i>	Name of the action
<i>user</i>	ID of the user involved in the action.
<i>pilot</i>	Identifier of the Pilot that uploaded the action
<i>location</i>	Location where the action is executed.
<i>position</i>	Geographical position at which the action took place.
<i>timestamp</i>	Date and time at which the action was executed.
<i>payload</i>	Set of measures values.
<i>rating</i>	Value defining the uncertainty of the inferred action (1.0: certain, 0.0: unreliable)
<i>extra</i>	Object containing additional, Pilot specific information that Pilots may want to add.

Table 4
Measure Common Data Format (CDF).

Property	Description
<i>user</i>	ID of the user to which the measures relate.
<i>pilot</i>	Identifier of the Pilot that uploaded the Measure
<i>interval_start</i>	Timestamp of the start of the time interval to which the measure relates.
<i>interval_end</i>	Timestamp of the end of the time interval to which the measure relates. Note: the following property duration can be used in alternative to this one
<i>interval_duration</i>	Duration of the time interval to which the measure relates. Note: the previous property interval_end can be used in alternative to this one.
<i>payload</i>	Object containing additional sub-properties, as needed to further describe the action.
<i>extra</i>	Object containing additional, Pilot specific information that Pilots may want to add.

enriches the gathered data applying spatial and temporal knowledge eliciting rules, which improve the semantic knowledge and ease the inference and querying processes. The SR is composed of two modules: the Cloud Data Acquisition Layer, which allows to manage large quantities of data in an efficient manner, and the Semantic Data Access Layer, which performs the semantization process over the stored data.

Finally, the Risk Analytics and Monitoring Dashboards block combines domain knowledge with data-driven machine learning

techniques to derive health, well-being and lifestyle behaviour quantifying factors and metrics able to predict the onset of MCI and frailty conditions, starting from Measures. It is internally composed of:

- the implementation of the City4Age MCI and frailty risk model (also referred to as the Geriatric Model – GM), which abstracts the main constructs of the domain in order to

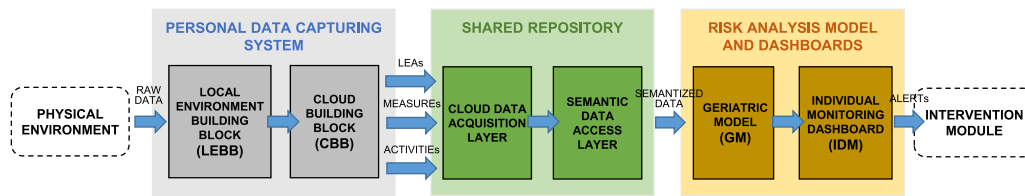


Fig. 2. Logical architecture of the proposed system. It consists of the Personal Data Capturing System (PDCS), the Shared Repository (SR) and the Risk Analysis Model and Monitoring Dashboards (RAMMD) modules.

provide a synthesized risk profile for each individual, or group/cluster within the observed population

- the Analytics REST API Service Layer, providing various interfaces to and from the Analytics, for other internal system modules and components, such as Intervention modules, and for applications and widgets targeted to end users (caregivers, physicians, researchers...)
- the Analytics Dashboards, in particular the Individual Monitoring Dashboard (IMD), an interactive collaborative tool used by geriatricians and other stakeholders to refine the risk detection process.

4.1. Personal Data Capturing System

The Personal Data Capturing System gathers large quantities of data from the physical environment through a sensing infrastructure, at home and city level. Relevant types of collectable data can be roughly grouped into the following categories:

- **User motility:** data related to user body activities, such as motion, rest, sleep, walking, etc.
- **Indoor/Outdoor localization:** data involved in the process of determining the position of the user inside a private or public indoor place, such as user's homes or shopping malls, pharmacies, churches, etc., as well as data related to the position of the user in outside places, like streets, parks, etc.
- **User/Environment interaction:** data related to user interaction with the surrounding environments, especially with home appliances (TVs, HVACs, etc.) and public services, for example public transportation.

Since several and heterogeneous technologies can be potentially involved in the process of gathering data for the categories listed above, the main rationale behind the adopted approach has been to define a reference solution for each gathering sub-system. Each of them is fully compliant with the LEBB-CBB architecture and starts from the sensing requirements expressed by the six pilot sites involved.

4.1.1. The motility sub-system

The reference architecture proposed for the User motility sub-systems (Fig. 3) is based on a low-cost prototypal wristband, associated with a smartphone, able to unobtrusively collect data related to the body motility of the elderly user [30]. With respect to the use of other commercial wristbands, this approach allows for a more direct control of sensors and communication interfaces, without involving third party APIs and services. In particular, the wristband, by exploiting its 9-axis inertial sensors, is able to classify the body posture of the elderly by analysing the collected data with a machine learning approach [31], which can be finely tuned according to user's needs. The result of the classification is then sent firstly to the smartphone, by exploiting the embedded programmable BLE interface of the wristband, and then to the CBB, through the smartphone Internet connection, for

further analysis. Therefore, the wristband, in conjunction with the smartphone, plays the role of the LEBB of the PDCS.

Typical outputs of this module are the BODY_STATE_START/BODY_STATE_STOP LEAs indicating the timestamp when the user enters and leaves a particular body state (i.e. still, walking, laying, etc.).

4.1.2. The Indoor/Outdoor Localization sub-system

The innovative solution proposed as a reference architecture for the Indoor/Outdoor localization sub-system (Fig. 4), is based on a wristband, associated with a smartphone, able to unobtrusively collect data related to user localization, both in indoor and outdoor environments, by using the proper technologies [32]. The wristband, in fact, is equipped with a BLE interface, which allows it to listen to BLE advertisements and to connect to a smartphone at the same time. In indoor environment, it can read the information broadcasted by a BLE beacon-based indoor positioning infrastructure (one beacon per each room) and, after calculating in which room the user is currently located by performing a classification algorithm based on RSSI [33], it sends this information to the smartphone and CBB, through the smartphone Internet connection, for further analysis. In conjunction with the smartphone, the wristband plays the role of the LEBB of the PDCS.

In outdoor environment, instead, it relies on the smartphone's GPS receiver to collect data about user's position and compare it with pre-defined Point of Interest (POI) locations, in order to generate the proper LEAs. However, if public commercial activities, such as shops, markets, pharmacies and so on, are equipped with BLE beacons, the wristband approach can be still used to better refine user's localization.

Typical outputs of this module are the POI_ENTER/POI_EXIT LEAs, indicating the location type and/or the GPS coordinates (by exploiting the GPS receiver of the smartphone).

It is worth noting that both functionalities of indoor localization and body motility can be implemented on the same wristband, if its hardware equipment supports MEMS, a BLE interface and a customizable firmware.

4.1.3. The User/Environment Interaction sub-system

Given the numerous ways in which elderly people can interact with their surrounding environment, in the context of this work, this task has been focused on unobtrusively monitoring the activation/deactivation of some household appliances, like oven, coffee machine, vacuum cleaner, washing machine, and so on, because their usage is tied to particular complex activities strictly related to precise GESs (i.e. housekeeping, laundry, preparing meals, personal hygiene, etc.). The reference architecture of the proposed home appliances monitoring system (Fig. 5) is based on a hybrid approach [34,35]. An unobtrusive smart meter constantly measures the overall energy consumption, by counting the blinks of the central power meter's LED; then, it communicates these values to a Cloud-based software module for appliance disaggregation of devices having a well-defined power fingerprint (like microwave oven, washing machine, fridge, etc.). In addition, in order to detect the usage of devices with low power consumption (for example TV or medical devices), especially when they



Fig. 3. Hardware infrastructure of the Motility sub-system. It is based on a prototypal wristband, paired with a smartphone, able to detect some body activities of the user.

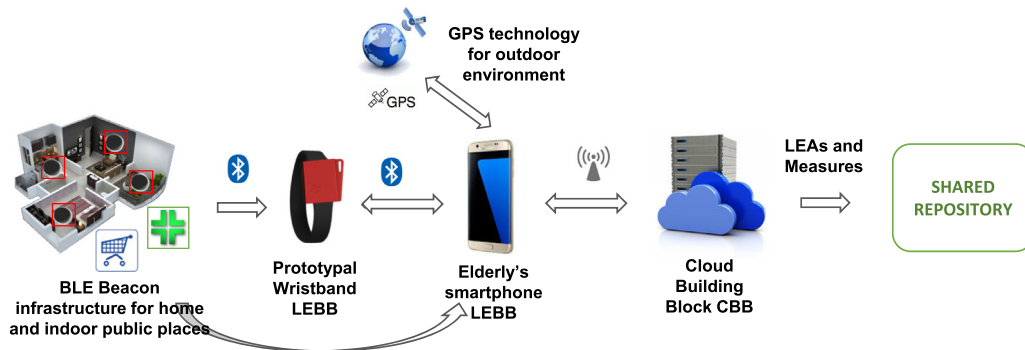


Fig. 4. Hardware infrastructure of the Indoor/Outdoor Localization sub-system. It is based on a wristband, associated to a smartphone, which interacts with a BLE beacon-based infrastructure for indoor positioning. For outdoor localization, it relies on smartphone's GPS interface.

are used at the same time of other appliances, one or more BLE-enabled or Wi-Fi-enabled smart plugs are used. They detect if the attached load is on or off and send this information to the CBB for further elaboration. By integrating power consumption data with data collected by other monitoring systems, like the user motility and indoor positioning system explained in Sections 4.1.1 and 4.1.2, it is possible to apply some activity recognition algorithms, in order to identify which type of complex activity the user has carried out.

4.1.4. The City4Age Data Capturing App

The smartphone represents the point of convergence for the sub-systems described in Sections 4.1.1–4.1.3 because, in addition to sharing its data connection to communicate the collected data towards the CBB, it groups the LEBB functionalities of the above sub-systems into a single application, that orchestrates all tasks. The City4Age Data Capturing App is a smartphone application that represents the bridge between external devices (such as wristband or smart plug) and the CBB. It is the first step in transforming user's behaviour into LEAs, according to the City4Age data model.

The City4Age Data Capturing App has a modular structure and implements the following functionalities:

- **Indoor localization:** the App interacts with the wristband (through the BLE interface) for detecting the indoor localization of the user within his/her house and in the monitored places in the City;
- **Outdoor Localization:** the App relies on the smartphone's GPS receiver to the user outdoor location;
- **Still detection:** by interacting with the wristband, the App is able to detect the periods of time in which the user is completely still while he/she is at home;
- **Walking detection:** by using sensors embedded in the smartphone and freely available software libraries, the App is also able to detect and track outdoor walking sessions of the elderly user;

- **Smart-plug interaction:** the App periodically scans and connects to the BLE smart-plugs installed at home to detect if the monitored device is switched on or off;
- **Phone usage detection:** the App tracks time and duration of all incoming, outgoing and missed calls
- **Data gateway:** the App collects data from the above modules, formats the related LEAs and forwards them to the CBB by exploiting the smartphone data connection. If the Internet connection is temporarily unavailable, the current LEAs are stored in a local repository on the device and resent as soon as the connection gets available again.

The City4Age Data Capturing App is self-starting, it runs on the background and does not require any interaction from the user. All data transmitted to the CBB are properly encrypted and protected, by using the common JWT token-based authentication approach, in conjunction with a HTTPS encrypted communication channel.

4.1.5. The Cloud Building Block

The Cloud Building Block is the first layer of data aggregation provided by the proposed architecture. It is implemented as a Cloud-based service for each City adopting the proposed approach. It is managed by local administrators and it deals with the collection and forwarding of LEAs and with the calculation of Measures to be sent to the Shared Repository. Although each Municipality is free to implement its own CBB service, the City4Age project proposes a reference implementation [36]. On the CBB, LEAs are stored in a local database that acts as a staging area; then, on a daily basis, LEAs are automatically normalized through *Extract, Transform, Load* (ETL) tools (like Pentaho⁶ Data Integration). These ETL processes consist of extraction, filtering, grouping, sorting, merging, performing computations, creating new fields, changing fields' format; these operations allow the removal of redundant and useless data, the computation of Measures, the creation of the proper CDF data objects. Finally, another

⁶ <https://www.hitachivantara.com/go/pentaho.html>.

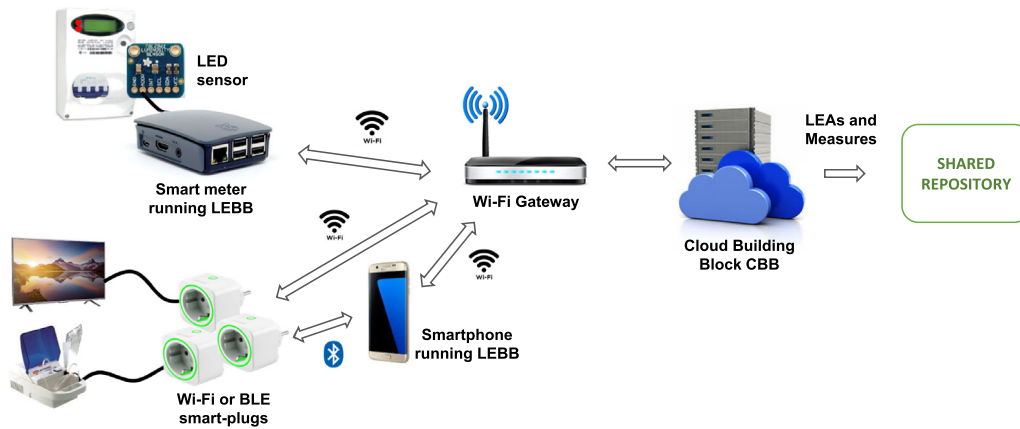


Fig. 5. Hardware infrastructure of the User/Environment Interaction sub-system. It consists of a Smart meter, which measures the overall power consumption of the flat, supported by a given number of smart plugs, used to monitor some low-power devices.

ETL process is launched to send LEAs and Measures to the Shared Repository.

4.2. The Shared Repository

The Shared Repository acts as the centralized repository for all data captured by the Personal Data Capturing System deployed in each city. The Shared Repository manages and annotates the data received from the cities, providing semantic meaning to the data by using a properly defined ontology [37]. The Shared Repository (see Fig. 6) is split into two main modules: (i) the Cloud Data Acquisition Layer, and (ii) the Semantic Data Access Layer.

The Cloud Data Acquisition Layer is used to acquire data from different sources, to store them in the Cloud, and to aggregate/transform them. The Cloud Data Acquisition Layer is the entry point for the IoT modules deployed in the cities. The aim of this module is to manage the connections between different IoT middle-wares, control the consistency of the data and persist it. The Cloud Data Acquisition Layer supports three different levels of abstraction for the data received from the cities:

- **Low-level Elementary Actions (LEAs)**, which represent short, conscious actions performed by the users (e.g. open the fridge, leave the house, take the bus or use the oven).
- **Activities**, which represent more complex events composed by LEAs (e.g. cooking a recipe or going to visit some family members) [38].
- **C4A Measures**, which are a summary of the aggregated actions of a user during a period of time (e.g. walked kilometres, number of calls or number of visits to family members).

This way the cities can decide which information granularity is better suited for their requirements or is more aligned with their existing sensing infrastructure. The data acquisitions process is done through three different endpoints: *add_action*, *add_activity* and *add_measure*.

The Semantic Data Access Layer enriches the stored data with semantic meaning. This module also uses a semantic rule reasoner to improve the stored information by inferring new statements using knowledge eliciting rules [39] (see Table 5 for some examples of the used rules). Additionally, this module also allows third parties to explore and query the stored data by using a REST, HTML and SPARQL endpoints. The aim of these endpoints is to allow third parties such as governments, companies or researchers to take advantage of the aggregated dataset, while maintaining the users' privacy.

When new data arrives to the Shared Repository, the workflow is the following:

1. The Personal Data Capturing System installed in a city performs a request to the Shared Repository using the endpoint provided by the Cloud Data Acquisition Layer.
2. The REST Server (Nginx) manages the request and creates an internal socket, pairing it with the Application Container (uWsgi⁷).
3. The Application Server (Flask) receives the request from the Application Container to the corresponding endpoint. The Application Server processes the request, performing the consistency checks on the received data and using the Object Relational Mapper (SQLAlchemy⁸) to store the data in the database (PostgreSQL⁹).
4. Once the data has been validated and stored, the Semantic Data Access Layer starts the process of giving semantic meaning to it. First, the Semantic Mapper (D2RQ¹⁰) extracts the data from the database and uses the semantic mappings (see Fig. 7 for an example of a mapping) to transform the data to semantic triples, using the City4Age Ontology [37].
5. The Semantic Rule Engine (Jena Rule Engine¹¹) receives the resulting triples and applies the knowledge eliciting rules (see Table 5 for an example of two rules) to infer more relevant knowledge and enrich the existing data.
6. The enriched data are sent to the RDF Server (Fuseki¹²) to make them available to third parties. The data in the RDF Server has been anonymized stripping it from any personal information, in order to protect the users' privacy. The RDF Server offers three different endpoints. A REST endpoint, an HTML endpoint, and a SPARQL [24] endpoint.

4.3. The Risk Analysis Model and monitoring dashboards

The MCI and frailty risk model designed in the scope of this work has been formalized as a hierarchical Bayesian network (Fig. 8), where a relatively small number (61 in total) of derived higher-level nodes (Geriatric Factor — GEF, Geriatric Sub-factor — GES, and Geriatric Factor Group — GFG) aggregate and summarize a larger number (151) of various underlying Measure

⁷ <https://uwsgi-docs.readthedocs.io/en/latest/>.

⁸ <https://www.sqlalchemy.org/>.

⁹ <https://www.postgresql.org/>.

¹⁰ <http://d2rq.org/>.

¹¹ <https://jena.apache.org/documentation/inference/index.html>.

¹² https://jena.apache.org/documentation/serving_data/.

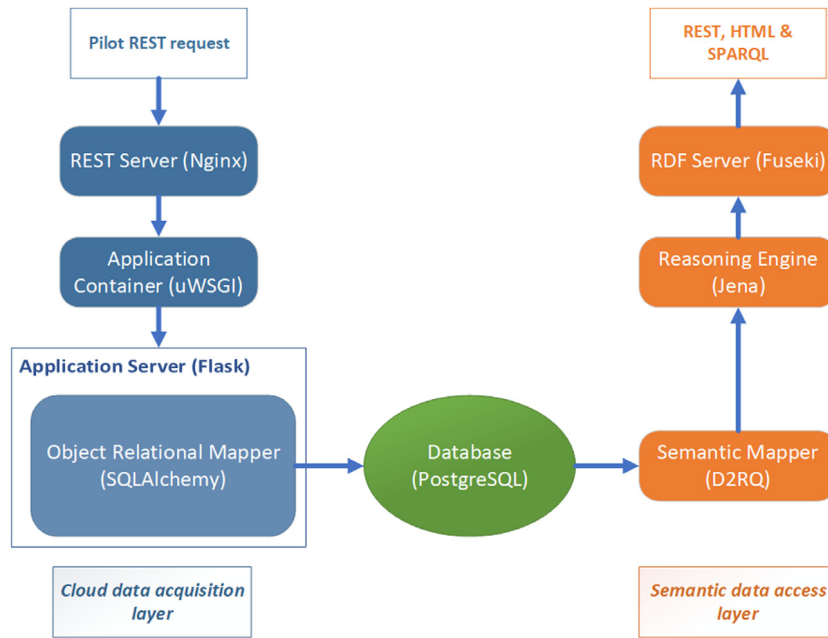


Fig. 6. Overview of the Shared Repository architecture. The Shared Repository is divided in two main modules, the Cloud Data Acquisition Layer and the Semantic Data Access Layer.

Table 5

Example of the knowledge-eliciting rules used by the semantic rule reasoner.

Rule ID	Rule body	Rule head
buildinglocation:	(?subject rdf:type vocab:location), (?subject vocab:location indoor "t"), (?subject vocab:location pilot id ?object)	(?subject schema:Place city4age:Building)
registeredstatus:	(?subject vocab:executed action date ?object) greaterThan (?object, "2014-04 21T07:08:41"8sd:dateTime) lessThan(?object, "2014-08-21T07:08:41"8sd:dateTime)	(?subject schema:actionStatus "registered")

1. map:city4age_ar_executed_action_id a d2rq:PropertyBridge;
2. d2rq:belongsToClassMap map:city4age_ar_executed_action;
3. d2rq:property hlifesci:identifier;
4. d2rq:propertyDefinitionLabel "executed_action id";
5. d2rq:column "city4age_ar.executed_action.id";
6. d2rq:datatype xsd:integer;

Fig. 7. Example of a semantic mapping used to transform the relational data in semantic triples.

types. The data analytics module works on the adopted combined knowledge- and data-driven approach based on this model, exploiting an ensemble of statistical, knowledge engineering and machine learning algorithms.

The model transforms and contextualizes the acquired sensor data into comprehensive determinants, commonly used and interpreted by geriatricians in the current knowledge and practice for the diagnosis and prediction of the onset of MCI and frailty conditions. The model also comprises knowledge expansion and refining mechanisms, in the general approach of studying and resolving classes of problem instances analytically [40]. In general, in the network presented in Fig. 8, overall MCI/FrailtyRisk (OVL) represents the top-level *query variable*, Measures represent *evidence variables*, while GEFs and GESs represent *hidden variables*. With its inner structure, the network is able to model:

- How the changes in acquired values of evidence variables influence the basic geriatric domains, particularly the acquired datasets of Measures of the behaviour of each observed elderly citizen (a provisional geriatric care recipient – CR). These include, for example, outdoor walking speed

(WALK_SPEED_OUTDOOR Measure, influencing the value of the derived Walking GES), or the number of visits to shops (SHOP_VISITS Measure, influencing the *Shopping* GES), or the daily number of meals (MEALS_NUM Measure, can influence both the *Ability to cook food* GES and the *Self-feeding* GES).

- How changes in geriatric functional features of behaviour, quantified by GESs, in turn influence a number of higher-level geriatric domains represented by GEFs. For example, GESs capture the ability and quality of walking (*Walking* GES, affecting the complete *Motility* GEF of a person), or ability to prepare own meals (*Ability to cook food* GES, constituting the *IADL* GEF).
- How the overall MCI and frailty level and risk status of a person is influenced by a number of functional factors and “macro-domains” represented by the GEF and GFG nodes respectively. For instance, the capability of the person to perform coordinated movement independently on its own (*Motility* GEF), or ability to carry out common Activities of Daily Living (*Basic ADL* and *Instrumental ADL* GEFs).

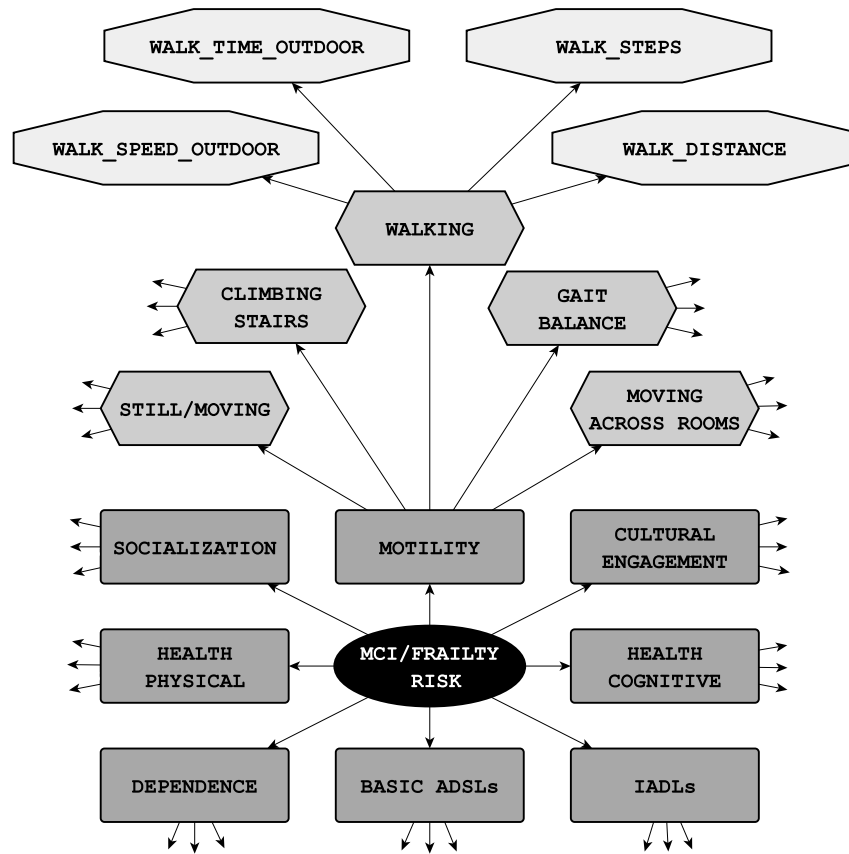


Fig. 8. An excerpt of network representation of the City4Age geriatric model. Main constructs: Measures (octagons), Geriatric Sub-Factors GES (hexagons), Geriatric Factors GEF (rectangles).

In the ongoing work, data-driven methods, such as Hidden Markov Model (HMM) [41] temporal clustering and latent feature recognition, are used in conjunction with manually explored correlations, data pivoting and mining, to discover additional significant and relevant interdependencies among (i) nodes, (ii) different Measures (including the pairs defined initially by domain experts as independent or unrelated), (iii) within specific clusters or subgroups, or personal datasets in the observed population, and/or (iv) in specific time periods/intervals, across all Pilot cities. The confirmed findings are then incorporated as new or alternative relations and nodes in the model. The model is used to compute a quantitative value for the overall MCI and frailty risk and specific risks associated with main geriatric functional domains, based on aggregation of Measures into Numerical Statistical Indicators (NUIs) and then into normalized comparable values for GESs, GEFs and GFGs. On the basis of monthly NUIs from continuous time series of daily or weekly Measure values, the values for GESs, GEFs, GFGs and OVL are derived, each as a weighted linear combination of underlying node values, normalized as a real number on Likert scale between 1 and 5, a commonly and intuitively understandable representation in geriatric practice. The computed data are then used to feed risk detection algorithms. To this end, time series analysis is applied to provide: (i) pattern recognition of historical data (detection of frequent types of sequences), and (ii) forecasting of future values based on historical trends.

In order to support further fine-grained risk and context assessments and decision making by the geriatrician and caregiver domain experts, the model formalization is exposed through a series of navigable hierarchic interactive diagrams presenting the time series of values of all abovementioned model variables (from Measures to GFG and OVL) for each observed CR, on the Individual

Monitoring Dashboard (IMD), a collaborative Decision Support System (DSS) environment (Fig. 9) provided in this work.

5. Performance analysis

This Section describes the tests carried out to evaluate performance of each module described in Sections 4.1–4.3. The performance considerations and envisioned deployment on Big Data volumes and flows have been taken into account from the start of conceiving and development of all system components, as well as the models. Tests related to PDCS have focused on sensing device's features and their non-functional requirements, as well as the amount of data produced by each individual on daily-weekly-monthly basis. The SR has been tested by measuring response time and percentage of used resources by its internal components (i.e. the Cloud Data Acquisition Layer, the Semantic Data Access Layer and the Rule engine). Finally, the effectiveness of the RAMMD has been evaluated by measuring the error between forecasted values and observed values. Section 5.1 contains a brief description of the hardware and software setup used for the execution of the reported tests.

5.1. Experimental settings

An instance of the Personal Data Capturing System has been deployed in the Lecce Pilot site of the City4Age project. Twenty-four elderly people (15 Women, 9 Men; 6 Couples, 12 Singles) have been equipped with a Samsung A5 2017 smartphone, running a revised version of City4Age Data Capturing App to overcome some technical limitations of the wristband. Elderly houses (17 houses) have been also equipped with a BLE beacon in kitchen, living room, bedroom and bathroom, for the indoor

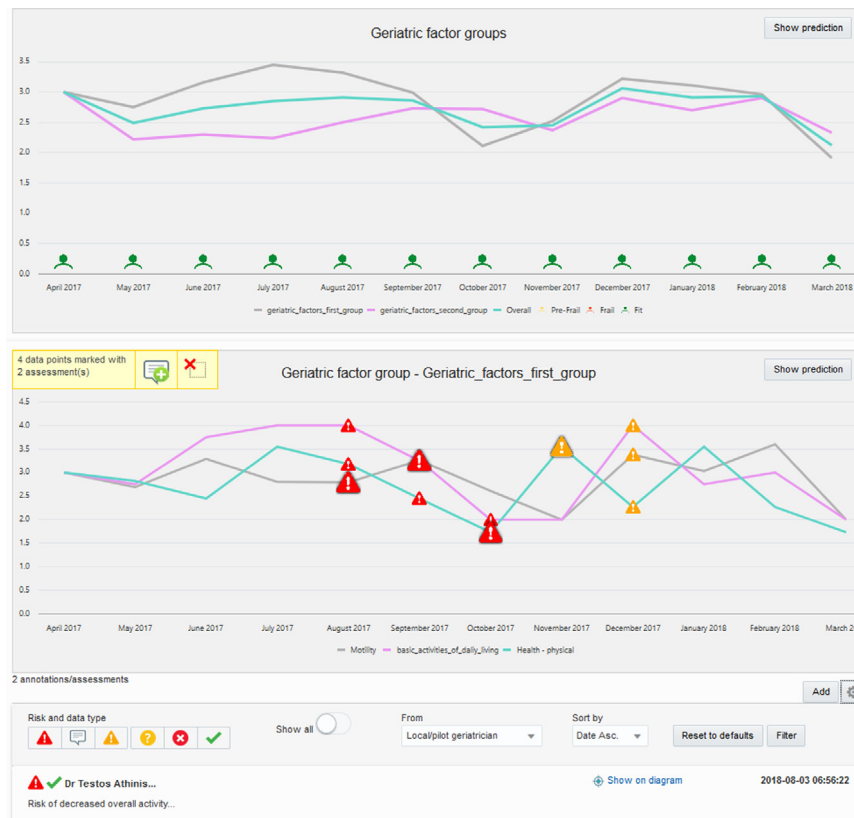


Fig. 9. Hierarchic interactive diagrams of the Individual Monitoring Dashboards. It shows GFG and GEF values and expert assessments on specific data points and sets.

localization sub-system and with two smart-plugs, with a TV and the washing machine attached to them, for the User/Environment Interaction sub-system. Some commercial activities in the city have been equipped with a BLE beacon in order to track the presence of the elderly in them. These places are: 3 Senior Centres, 2 Bakeries, 5 Pharmacies and 7 General Practitioners (GPs).

The CBB is based on the following components, running on the same machine:

- An Apache Tomcat v7.0 (JDK 7) servlet container where the CBB REST API is deployed;
- An Ubuntu Server machine (14.04 LTE) with WSO2 ESB, BRS and AS modules;
- An Ubuntu Server machine (14.04 LTE) where Pentaho Data Integration (PDI) 7.0 is deployed;
- An Ubuntu Server machine (14.04 LTE) where MongoDB 3.2¹³ is deployed.

The Shared Repository tests have been executed in a dedicated server based on an Intel(R) Xeon(R) E5606 processor at 2.13 GHz of clock speed, with 8 GB of RAM memory at 1333Mhz clock speed (In dual channel mode) and a 500 GB ATA disk with maximum transferred speed ratio at 300 MB/s and 7200 nominal media rotation rate.

Table 6 summarizes the data stored in the Shared Repository and used for the performance analysis of Section 5.3. This data was captured during the City4Age deployment in the six project cities during the pilot phase (see [42] for more detailed information).

Using the real data captured by the six pilot cities in the experiments ensures the applicability and fairness of the results.

The real usage of the Shared Repository during the piloting phase can be seen in Fig. 10. We have used these data to model the experiments in order to simulate the real conditions.

Tests related to the performance of the Risk Analysis and Prediction are based on Measures data coming from Birmingham pilot and all tests have been executed on the Analytics sandbox VM based on dual Intel® Xeon® E5-2603 type processor cores at 1.7 GHz clock speed and 128 GB of DDR4 RAM at 2400 MHz clock speed. The Analytics run over the directly accessed data stored in the Shared Repository (PostgreSQL v10), utilizing Hibernate v5 Object-Relational Mapper wherever viable in all Java EE8 code implementations, as it is the complete Analytics REST API Service Layer, and the Monitoring Dashboards, and most of the analytics logic, using the available suitable algorithm and ML libraries, like the Signaflo library for time series analysis in Java. Latest recently released version 5 of Oracle-sponsored GlassFish (Sept. 2017¹⁴) is the main application server running the Analytics REST Services, including the back-end that supports the Analytics Dashboards, with the advanced front-end data visualization and annotation features of the Dashboards being developed in Oracle JET¹⁵ open-source JavaScript framework.

5.2. Performance analysis of the Personal Data Capturing System

From a performance point of view, the most critical component of the sensing layer of the PDCS is the device chosen for the implementation of the wristband-based approach for motility and indoor localization, explained in Sections 4.1.1 and 4.1.2. At the time the City4Age project started (December 2015), the only

¹⁴ <https://javaee.github.io/glassfish/>.

¹⁵ <https://www.oracle.com/webfolder/technetwork/jet/globalSupport-releaseNotes.html>.

¹³ <https://www.mongodb.com/>.

Table 6
Data used during the experiments for the Shared Repository.

City	LEAs	C4A measures	Registered users
Birmingham	178	159,581	35
Athens	0	457,848	44
Lecce	1,005,835	280,135	24
Madrid	29,777	2125	56
Singapore	55,932	8,569	19
Montpellier	310,589	49,864	18

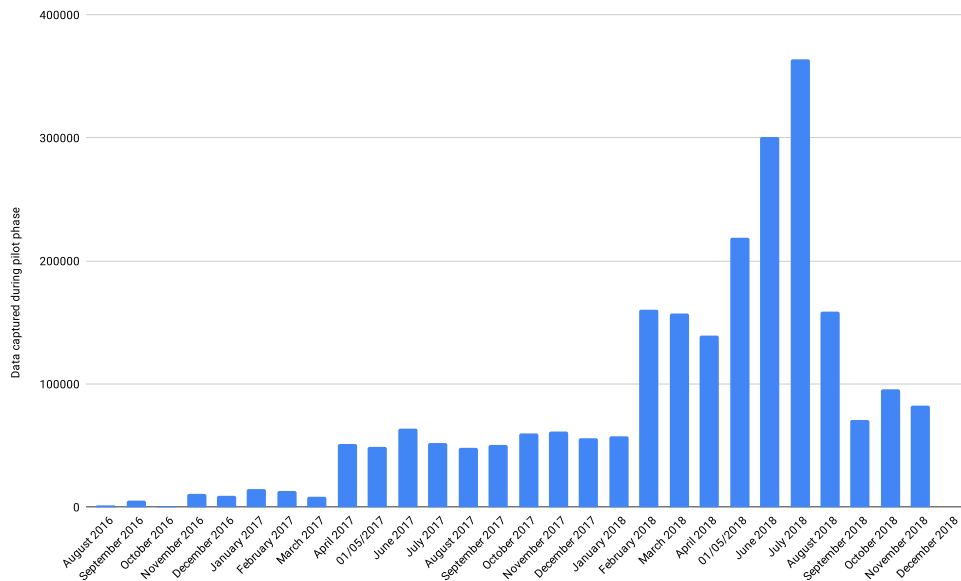


Fig. 10. Distribution of the Shared Repository usage during the piloting phase.

device suitable for project's needs was the CC2650STK prototypal board, also known as SensorTag,¹⁶ produced by Texas Instruments. It is based on an open platform that allows the definition of customized algorithms for reading and elaborating raw data from a set of embedded sensors, such as MEMS accelerometers and gyroscopes, temperature, humidity and light sensors, etc. Moreover, it is equipped with a programmable BLE interface, which allows the communication with several devices based on this standard protocol, like smartphone and beacons.

Once the algorithms for detecting body motility and indoor localization have been implemented on the SensorTag, real life validation showed some functional and non-functional limitations described in the following:

- **Power consumption:** the algorithm based on a machine learning approach used for the motility detection makes an extensive use of the MEMS accelerometers, while the indoor positioning algorithm heavily relies on the BLE interface. Their combined working cycles require a quite big amount of power that rapidly depletes the CR2032 coin battery (240 mAh) that feeds the SensorTag, making the device barely working the whole day;
- **Battery replacement:** replacing the battery in the SensorTag requires removing the rubber protection, opening the plastic case, replacing the battery and reassembling the case. This sequence of operations can be quite difficult for elderly people;
- **Disconnections and data buffering:** when the wristband is out of the range of the smartphone, the BLE connection between the two devices is temporary broken. It happened

very often in same houses when the smartphone was in the opposite room with respect to the user wearing the wristband. Although data buffering techniques have been implemented both on the SensorTag and in the City4Age Data Capturing App, the limited memory of the wristband (up to 148 KB of memory for code and data) actually allows the buffering for at most a couple of hours of activity;

- **Form factor:** the device's form factor has been considered uncomfortable and cumbersome by some elderly, who were reticent to wear it;
- **Waterproofness:** the SensorTag is not waterproof and it has been considered as a great hindrance during daily activities, like personal hygiene, laundry, washing dishes, etc.

Taking into account these functional drawbacks, which actually limit the usefulness of the device in doing its task, and the non-functional user requirements, which could limit the correct use even of a properly working wristband, in order not to affect the operation of the whole project, it was decided not to continue with the wristband-based approach. Instead, it has been decided to implement the indoor localization and the body motility systems directly on the smartphone (together with outdoor localization already implemented) and invite users to carry always the smartphone with them, even in indoor environment, by providing them with a belt clip case. By doing so, all the requested collecting features are implemented on a single device with high computational capabilities and power autonomy. Furthermore, the smartphone OS allows to create customized application interacting with open libraries (like Google Awareness APIs¹⁷) that provides ready-to-go functionalities for automatically detecting, for example, when the user is still or is walking.

¹⁶ http://www.ti.com/ww/en/wireless_connectivity/sensortag/.

¹⁷ <https://developers.google.com/awareness/>.

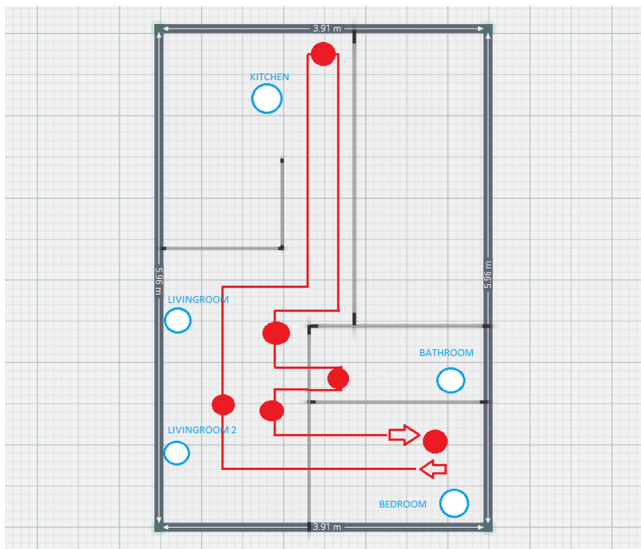


Fig. 11. Environment setup for the tests of the smartphone based Indoor Localization system.

This fall-back plan, obtained at almost no cost since the smartphone was already part of the equipment of each user participating to the project experimentation, has allowed to generate a constant data flow to feed the SR and, consequently, the risk detection algorithms. In addition, it has demonstrated the flexibility and versatility of the whole PDCS architecture, which is completely device and technology agnostic, provided that the LEA and Measure's CDFs are respected as output format of the data gathering process.

The proposed Indoor Localization system has been validated through some supervised tests. A small apartment of approximately 70 m² has been equipped with a BLE beacon (BlueBeacon Mini¹⁸) for each room (except for the Livingroom, where two beacons was placed, given its breadth), as shown in Fig. 11 (white circles). The beacons have been placed at one metre from the ground. Then, a path within this environment has been defined and the testing user, equipped with the smartphone (Samsung A5 2017) in his trousers' right pocket, has followed it, stopping for a while in the spots indicated with the red full circles on the map (Fig. 11). The user remained in each position for 3 BLE scanning cycles (5 s for each cycle) and the path was repeated for 8 times. The number of false positives for each room detection has been measured and shown in Table 7.

Results show that, by accurately choosing the beacon position inside the room, it is possible to achieve an accuracy in detecting the current room above the 86% on average.

It is worth noting that the validation presented above is only an excerpt of the many tests that have been performed and that are currently being performed on the Personal Data Capturing System, in particular on the Indoor/Outdoor Localization and Motility sub-systems. Other more accurate results will be presented in upcoming works.

From a data throughput point of view, the first months of experimentation of this smartphone-based PDCS implementation allowed to note that the quantity of data transmitted to the CBB depends on how the elderly moves in monitored places and how he/she is physically active. In fact, since each detection sub-system triggers a LEA only when a change of state is detected, if the user frequently changes room and frequently alternates

periods of body activity with periods of rest, then a high number of LEAs are detected and sent. On the contrary, when the user performs prolonged periods of continuous activity (or inactivity) in the same location, then the rate of state changes is low, therefore this situation corresponds to low data transmission. The same holds for LEAs related to the usage of the phone for calling, the TV and the washing machine: the more the user activate/deactivate them, the more LEAs are sent. In terms of data volume, the most numerous LEAs are those related to the walking outdoor use case. In order to track user's speed and distance, when a walking body state is recognized by the related module of the City4Age Data Capturing App, a BODY_STATE_IN reporting LEA is sent every 5 s, containing the GPS position and speed of the user. Therefore, a 30 min walk produces about 360 LEAs.

Table 8 gives an overview of the amount of data related to a typical user, summarized by analysing the data produced by the most representative users involved in the first three months of experimentation in the Lecce pilot. The table reports the number of LEAs, per each category, produced by a typical user on a daily, weekly and monthly basis. It is worth noting that the number of LEAs does not scale up linearly with time, since some daily activities are not performed every day.

In Table 8 it can be seen that each person produces about 1300 LEAs per day. On average, each LEA contains about 350 Byte of data, therefore the expected total amount of data generated per day by each elderly is in the order of 0.445 MB, with a projection of 14 MB per month. If a city has a population of 1.000.000 inhabitants, of which 25% are 65+ years old, this means that the potential volume of data generated in a year is about 42 TB. Concerning the LEBB, which represents each single data source, this daily volume is perfectly manageable, both in terms of buffering size and data bandwidth; however, the CBB must be properly setup in order to satisfy all concurrent requests, taking into account the actual number of involved citizens.

Particular countermeasures had to be taken in order to overcome some issues related to an improper use of the smartphone by elderly people. Sometimes, in fact, they inadvertently shut down the app for data collection, or shut down the Bluetooth, the GPS or the mobile data connection interfaces from the operating system, making impossible the data collection and communication, therefore affecting data throughput and the validity of the risk detection algorithms.

Regarding Measures' throughput, currently the Lecce pilot foresees 44 Measures. They are computed on a daily basis starting from the collected LEAs and sent to the Shared Repository (with the same frequency). If, during the day, there have not been produced LEAs for the computation of a given Measure, it is sent anyway, with a default zero value. Therefore, the throughput of Measures is constant over the time.

5.3. Performance analysis of the Shared Repository

The Shared Repository is the cloud infrastructure that receives the data from all the cities taking part in the City4Age project. In this section we analyse the different working modes of the Shared Repository and how different configuration decision can affect the system performance. The results are discussed in Section 6.2, where we analyse the advantages and disadvantages of each working mode and offer guidelines for the system usage. All the experiments have been modelled using the real data captured from the pilot cities as discussed in Section 5.1.

The tests defined to analyse the Shared Repository performance have been divided in two groups: (i) the Cloud Data Acquisition Layer tests and (ii) the Semantic Data Access Layer tests. To analyse the Cloud Data Acquisition Layer two different experiments have been performed, aimed to assess its performance while receiving multiple C4A Measures in a single call

¹⁸ <https://blueup.myshopify.com/products/bluebeacon-mini>.

Table 7

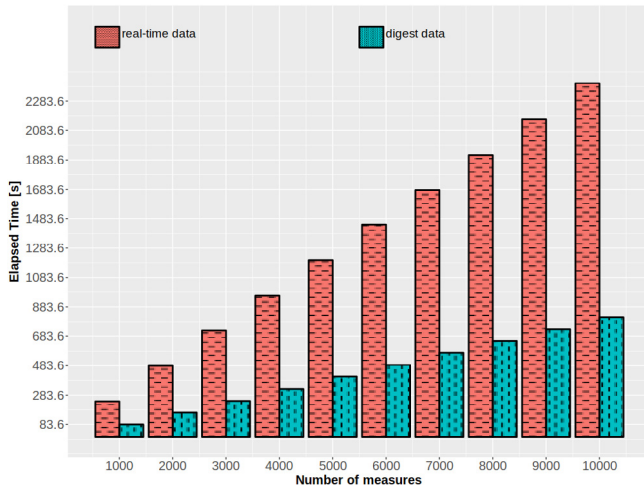
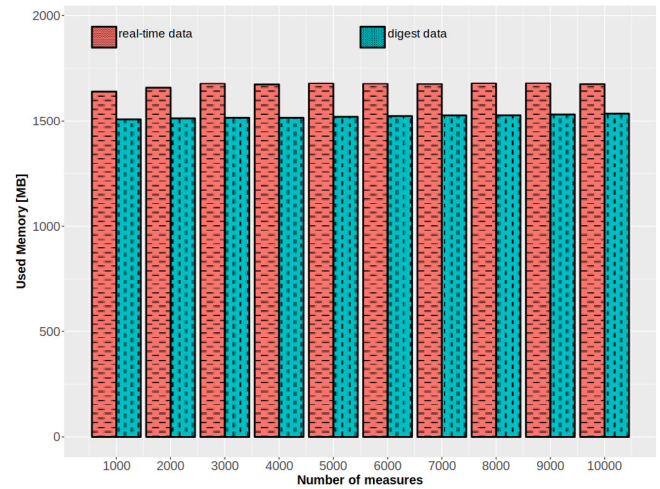
Error rate of the smartphone based Indoor Localization system in detecting the current room.

Room	Test1	Test2	Test3	Test4	Test5	Test6	Test7	Test8
Bedroom	1	2	0	1	0	0	2	0
Livingroom	0	0	0	0	0	0	0	0
Kitchen	0	0	0	0	0	0	0	0
Livingroom	0	0	0	0	0	0	0	0
Bathroom	2	1	0	1	0	1	0	1
Livingroom	1	1	0	1	0	1	1	0
Bedroom	0	0	1	1	0	1	1	1
False positives	4	4	1	4	0	3	4	2
Error percentage	19,05%	19,05%	4,76%	19,05%	0,00%	14,29%	19,05%	9,52%
Average error percentage	13.10%							

Table 8

Average amount of LEAs produced by each subject, on a daily, weekly and monthly basis.

LEA	Day	Week	Month
POL_ENTER/POL_EXIT for Home indoor related POIs	40	300	1340
POL_ENTER/POL_EXIT for City monitored POIs	6	40	170
BODY_STATE_START/BODY_STATE_STOP for Still state	22	180	700
BODY_STATE_START/BODY_STATE_IN/BODY_STATE_STOP for Walking state	1180	8000	33000
APPLIANCE_ON/APPLIANCE_OFF for TV	12	90	350
APPLIANCE_ON/APPLIANCE_OFF for Washing Machine	2	2	4
PHONE_IN/OUT_START/STOP for calls	6	58	220
Total	1268	8670	35784

**Fig. 12.** Elapsed time while sending request to the Cloud Data Acquisition Layer. The bars with the horizontal pattern show the real-time mode and the bars with the vertical pattern the digest mode.**Fig. 13.** Used memory while sending request to the Cloud Data Acquisition Layer. The bars with the horizontal pattern show the real-time mode and the bars with the vertical pattern the digest mode.

where the measures are sent in an integrated batch file (**digest mode**) or receiving the same amount of C4A Measures in multiple concurrent calls (**real-time mode**). The Shared Repository supports both modes, allowing each city to select one. The number of individual user Measures sent have been varied, comparing both modes with the same number of C4A Measures (taking into account the real data usage during the pilot phase). This allows to evaluate what is the preferred behaviour for the cities while uploading the user data. While performing these experiments both the response times (see Fig. 12) and the used memory (see Fig. 13) have been measured.

For the Semantic Data Access Layer, both the query performance of the Shared Repository and the performance of the Rule Engine have been evaluated. In the case of the query performance, a comparison between retrieving the same information via SQL and SPARQL [24] queries has been carried out. The Semantic Data Access Layer has multiple endpoints that allow the data to be queried using either of the options. The SPARQL endpoint allows for a more expressive syntax, retrieving the data as an

ontology. The number of elements retrieved by the queries has been varied, comparing the same number of elements for both systems. While performing these experiments both the response times (see Fig. 14) and the used memory (see Fig. 15) have been measured.

In the case of the Rule Engine, the usage of a persistence method (Apache Jena – TDB [43]) versus a volatile storage model (**non-TDB**) has been analysed. The TDB is a component of the Jena framework used to store and query RDF data, while supporting the full range of the Jena APIs. The TDB can be used as a high-performance RDF store on a single machine. On the other hand, the volatile storage model for the rules only used temporary files. The Shared Repository can be configured to use either of the working modes. To analyse the difference between these two approaches we have measured three different metrics during the execution of the rules: the memory usage variation along the execution (see Fig. 16), the CPU usage variation along the execution (see Fig. 17), and the elapsed time to execute all rules (see Fig. 18). The test has been carried out by using all the

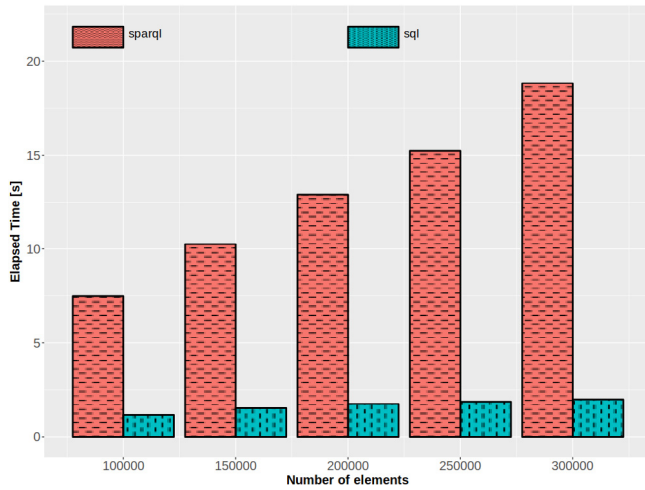


Fig. 14. Elapsed time while querying the data. The bars with the horizontal pattern show the SPARQL queries and the bars with the vertical pattern the SQL queries.

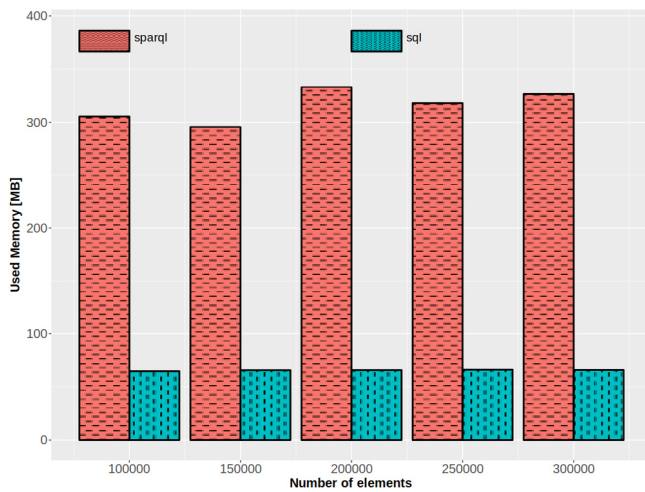


Fig. 15. Used memory while querying the data. The bars with the horizontal pattern show the SPARQL queries and the bars with the vertical pattern the SQL queries.

available data to better test the performance. It combines both the semantic entailment and the ad-hoc rule execution. On a real environment the process would be done incrementally as new data arrives to the repository.

All these experiments have allowed us to test the most critical elements in the Shared Repository performance wise. In the case of the Cloud Data Acquisition Layer and the query mode of the Semantic Data Access Layer, the system allows to configure which option will be used (real-time vs digest mode, and SPARQL vs SQL) by each deployment, allowing the users to balance the performance versus extra features. In the case of the Rule Engine, the TDB mode offers more advantages both in performance and features. For this reason, the TDB mode is the only supported mode in the final version of the Rule Engine. These points are further discussed in Section 6.2.

5.4. Performance validation of risk analysis and prediction through monitoring dashboards

In this section we show how prediction models of care recipient's risk associated with deterioration in individual geriatric

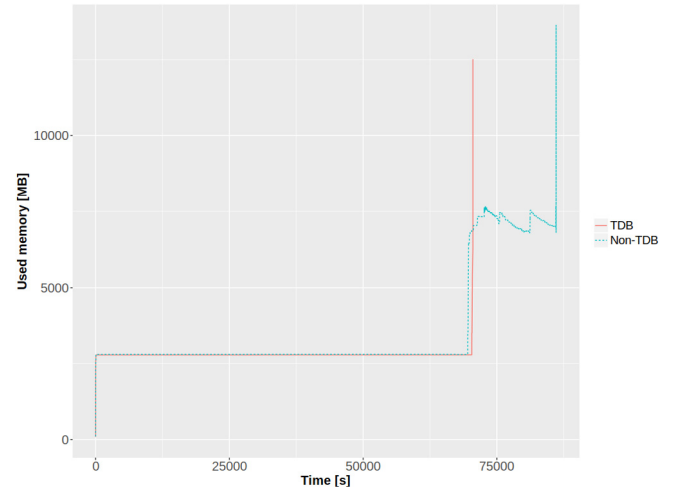


Fig. 16. Memory usage of the Semantic Rule Engine while executing the rules (persistent (TDB) vs volatile mode (Non-TDB)).

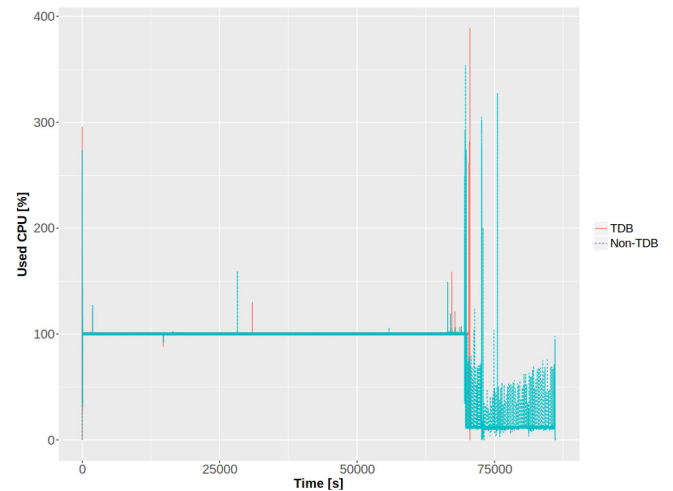


Fig. 17. CPU usage of the Semantic Rule Engine while executing the rules (persistent (TDB) vs volatile mode (Non-TDB)).

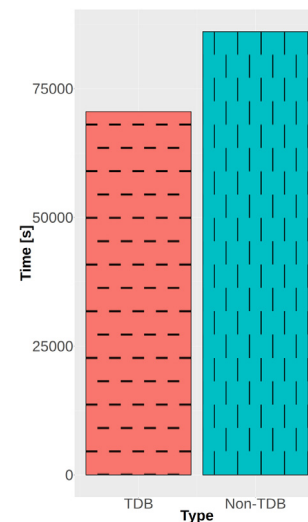


Fig. 18. Elapsing time for the rule execution (persistent (TDB) vs volatile mode (Non-TDB)).

domains, as well as MCI and frailty, were developed and assessed. In particular, we used AutoRegressive Integrated Moving Average (ARIMA) [44] models to fit and predict (forecast) three future values of time series comprising monthly values of high-level factors and groups of the geriatric model, namely GES, GEF, GFG and OVL. The choice of the forecast horizon was derived from the geriatric health care expertise, according to which 3 months is a critical period for detecting early signs of deterioration and applying timely health care interventions. We quantified how close model predictions are to the actual outcomes using standard forecast accuracy metrics i.e. Mean Error (ME), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

ARIMA models cater to a collection of standard structures in time series data [45] and as such have been used in a number of various fields [46,47], including healthcare and well-being analytics and prevention [48–50], for performing comprehensive time-series forecasts.

Specifically, a rule of thumb in relevant ARIMA applications is that about two years of monthly values are needed to enable the model to “learn” repetitive seasonal patterns. Given that our data is acquired for less than two years, we placed the focus in this work on the non-seasonal ARIMA models. These models combine time series differencing with autoregression and moving average model [51], i.e. a time series x_i is ARIMA(p, d, q) if it can be represented as in (1):

$$x_i^{(d)} = \alpha + \phi_1 x_{i-1}^{(d)} + \dots + \phi_p x_{i-p}^{(d)} + w_i + \theta_1 w_{i-1} + \dots + \theta_q w_{i-q} \quad (1)$$

with $\phi_p \neq 0$, $\theta_q \neq 0$ and $\sigma_w^2 > 0$. The parameters p and q are called autoregressive and moving average orders, d is degree of differencing involved, w_i is a Gaussian white noise sequence and α represents mean (called “drift” when $d = 1$). To find the optimal model, we implemented a function that conducts a search over possible models within constraints provided for p, d, q and returns the model with the lowest Akaike Information Criterion (AIC) [52] value. The steps of the algorithm are shown in Fig. 19. The prediction models were built and deployed using Java time series library [53].

The analysis included 1615 time series comprised of consecutive monthly geriatric factor values (GES, GEF, GFG and OVL) acquired for care recipients of the Birmingham pilot. Each of the time series contained 18 data points (from January 2017 until July 2018), including imputed values in cases where the value of variable is missing, and each is represented with a real number on the Likert scale (1–5). Missing values are imputed using the weighted moving average (WMA) algorithm with window size of 2, i.e. 2 left and 2 right values are taken into account. If all observations in the current window are missing, the window size is increased until there are at least two values present. The rationale behind this choice is simple; as the number of acquired observations is arguably too few to allow exploiting seasonal patterns in health-related behaviours, an obvious alternative to approximate missing observations is to use observations made in a couple of preceding and following months. After experimenting with different weights, we obtained values $\frac{1}{2}$ for observations at positions $i - 1$, $i + 1$ and $\frac{1}{4}$ for observations at positions $i - 2$, $i + 2$. Thus, a missing value at a position i in time series x was computed via the following equation (2):

$$x_i = \frac{2}{3} * \left(\frac{1}{4} x_{i-2} + \frac{1}{2} x_{i-1} + \frac{1}{2} x_{i+1} + \frac{1}{4} x_{i+2} \right) \quad (2)$$

It was observed that the optimal model for approximately 30% of analysed time series was found to be the random walk model i.e. ARIMA (0, 1, 0).

The following standard metrics (3) were used to evaluate model forecasting performance:

$$\begin{aligned} ME &= \sum_{i=1}^n \frac{y_i - x_i}{n}, & MAE &= \sum_{i=1}^n \frac{|y_i - x_i|}{n}, \\ MAPE &= \frac{100\%}{n} \sum_{i=1}^n \left| \frac{y_i - x_i}{x_i} \right| \end{aligned} \quad (3)$$

where y_i is a forecasted value, x_i is an observed value and n is the number of forecasted points. MAPE is the most commonly used error metrics which expresses by how many percentage points the forecasts are “off the mark” compared to the actual values. The (relative percentage) forecasting accuracy can be thus expressed as MAPE deducted from 100% (100% – MAPE). The mean absolute error, or MAE, is calculated as the average of the absolute forecast error values; it is in the original unit of predicted values. A MAE of zero indicates no error. Mean error (ME), also called the forecast bias, shows whether the model has tendency to over forecast (positive error) or under forecast (negative error).

Fig. 20 provides a summary of performance measures indicating predictive capability and accuracy of the forecasting models. In particular, the figure shows average accuracy metrics values for forecasts from August 2017 until July 2018. Each of the sub-diagrams contains three lines, two of which present forecasting errors aggregated over GES, GEF and GFG, with forecast horizon of 1 month (dotted lines) and 3 months (dashed lines). For the sake of clarity, for the OVL factor, representing the overall frailty of a care recipient, a single solid line is used to present forecasting errors with the horizon of 3 months. The reason behind separating OVL from remaining geriatric factors is due to being the main parameter exploited in the prediction and assessment of MCI and frailty risk by the geriatric experts and caregivers in individual monitoring.

The average percentage accuracies of forecasts with the 3-month horizon for the period from August 2017 to January 2018 are 87.82% (aggregated over all factors) and 88.78% (aggregated over OVL). In the following six months, from February 2018 until July 2018, falling into the second year of monitoring, the average accuracy scores rose to respectively 89.36% and 91.13%. Average MAE of 0.30 is the lowest for the OVL forecasts. Finally, the average values of MEs, of –0.04, –0.06 and –0.07, corresponding respectively to forecasts aggregated over all factors with forecast horizons of 1 and 3 months and the OVL factor with a horizon of 3 months, suggest that obtained forecasts are close to unbiased in all three cases.

6. Discussion

In this Section, results illustrated in Section 5 are recalled and further commented on a global scope, in order to highlight critical issues for each component and to provide the best overall system configuration to overcome such problems.

6.1. The Personal Data Capturing System

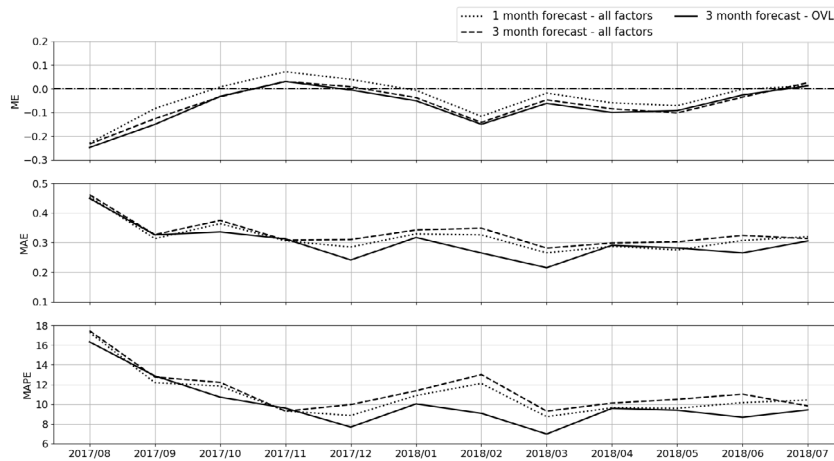
From a data capturing perspective, the PDCS has been based, since the beginning, on a low-cost, unobtrusive and best-effort approach. The goal was to improve the acquisition of data related to elderly behaviour by using unobtrusive technologies that do not interfere with everyday life activities, but able to provide digitalized data to feed automatic risk detection algorithms. These algorithms are used to define a risk profile for each subject with respect to MCI and frailty conditions, in order to support geriatricians during their common practice and to provide customized interventions.

Algorithm 1 Finding optimal ARIMA model

```

1: procedure FINDOPTIMALARIMA
2:    $aic \leftarrow \infty$ 
3:   for  $p \leftarrow 0$  to 3 do
4:     for  $d \leftarrow 0$  to 2 do
5:       for  $q \leftarrow 0$  to 3 do
6:          $model \leftarrow \text{fit}(\text{arima}(p, d, q, \text{allow\_drift} \leftarrow \text{True},$ 
7:                                $\text{allow\_mean} \leftarrow \text{True}), x)$ 
8:          $aic\_curr \leftarrow \text{compute\_AIC}(model)$ 
9:         if  $aic\_curr < aic$  then
10:            $model\_opt \leftarrow model$ 
11:            $aic \leftarrow aic\_curr$ 
12:   return  $model\_opt$ 

```

Fig. 19. Pseudo-code for finding optimal ARIMA model.**Fig. 20.** Resulting metrics of errors in forecasting using ARIMA method on data aggregated from Birmingham pilot.

For these reasons, the main challenge of PDCS has been the adoption of the wristband-based approach for body motility and indoor localization. As deeply discussed in Section 5.2, this approach, although being effective and valid, is highly device dependent, especially from a power autonomy point of view. The investigation aimed to make the wristband approach useable in real life is in an active phase. The first step is to search for a rechargeable battery wristband, which allows users an easy recharging procedure. General hardware and software requirements for such device are: a programmable BLE interface, embedded inertial MEMS sensors, rechargeable and long-lasting battery, open platform or open APIs for customized app development. Many commercial fitness tracker wristbands provide inertial sensors and (often) open APIs to retrieve collected data. However, none of them provides customizable access to BLE interface to implement the indoor localization system. Prototypal wearable solutions are more suitable for this purpose.

However, taking into account the whole lifecycle of the City4Age project, which provides a set of interventions based on collected data, mainly consisting in SMS, WhatsApp and Messenger text messages, also these aspects could be considered in order to find a solution that minimizes costs on a global scale. Considering the original Lecce pilot setup, for the data collection it foresees the wristband and the smartphone: the latter, beside acting as a gateway for data forwarding, acts also as a terminal for visualizing the customized intervention messages.

Recent technological advances, and the resulting price fall, in the field of high-performance smartwatches (like Huawei Watch 2, Apple Watch, Samsung Gear) made it possible to include in a single wearable device inertial MEMS, BLE and GPS interfaces,

together with a 4G/LTE module, allowing them to be independent from a paired smartphone for calls and data connectivity to the cellular network. Moreover, they also have open OS for creating customized standalone application, which can run completely on the smartwatch. Therefore, both the Indoor/Outdoor localization system and the body motility system can be completely implemented on the smartwatch, which can also manage the data transmission phase towards the local server, without needing an associated smartphone. Finally, the 4G interface can also be exploited for interventions, by using phone calls, SMS and third-party messaging apps.

In this perspective, with a look towards the exploitation of the entire City4Age project, the possibility to replace the couple smartphone + wristband for data collection, data forwarding and intervention displaying, with a single 4G smartwatch (e.g. the Huawei Watch 2) could be a valid alternative. Such device, in fact, can offer almost the same capabilities of a smartphone for implementing the indoor localization and the motility algorithms, although with some limitations, but natively including the GPS feature for outdoor localization. All collected data can be sent to the CBB through the 4G interface embedded in the smartwatch (or a paired smartphone when available), thus allowing a continuous data flow. By exploiting these communication interfaces, the smartwatch can become also a terminal for interventions, being it able to receive and send SMS and messages of the available IM applications. Obviously, the battery duration must be considered also in this case, in order to guarantee that the smartwatch can operate uninterruptedly at least from waking up to bedtime. A positive feature of such smartwatch is the easiness of the recharging procedure, very similar to the smartphone one, to which elderly people are accustomed.

Finally, regarding the User/Environment interaction sub-system, in order to foster a more effective smart city approach, a valuable feature would be to collect information about power consumption directly from energy provider companies, by interconnecting with their Cloud services that are becoming more and more common. In recent years, in fact, many providers offer Web Services that give the users the possibility to access their consumption data, read from the central metre in their flats (generally) every 15 min and stored in a Cloud platform. This would allow to avoid the installation of the smart meter in each house, but to reuse a publicly available service, although with a lower resolution in power measurement.

6.2. The Shared Repository

Both main modules of the Shared Repository (the Cloud Data Acquisition Layer and the Semantic Data Access Layer) need to be analysed separately to better assess their performance and limitations. In the case of the Cloud Data Acquisition Layer, the most influencing factor is the selected mode to send the data collected by the Personal Data Capturing System to the repository. The Shared Repository supports two modes: the real-time mode, in which each computed measure is sent to the repository in real time and the digest-mode, in which a set of measures are sent in the same request at some predefined time periods. In terms of performance, using the real-time mode takes significantly more time to process the same amount of measures than the digest mode (see Fig. 12), but none of the modes offer a significant advantage regarding the used memory (see Fig. 13). The digest-mode requires fewer requests to the Cloud Data Acquisition Layer, thus resulting in shorter times to send the same amount of data to the Shared Repository. Functionally, the decision of using one of the modes depends on the requirements of each city. Employing one of the modes over the other will be determined by the needs of the city, having to balance the need for real-time analytics with the resource usage. In many cases, the city will only be interested in the aggregated information to analyse the risks related to the elders' behaviour. In these situations, using the digest mode will be the recommended option, as it will reduce the processing requirements of the Shared Repository.

In the case of the Semantic Data Access Layer, two are the factors that will influence the performance: the technology used to query the data and the execution of knowledge eliciting rules. In the first case, the Shared Repository allows to use either SPARQL queries or SQL ones. In terms of performance, SQL queries are faster (see Fig. 14) and use less memory (see Fig. 15). When retrieving 300,000 elements, the SPARQL query will take more than ten seconds. This operation times must be considered by the cities when deciding to use the Semantic Data Access Layer. The memory usage differences are not so relevant and should not be a deciding factor when choosing one of the technologies. Functionally, the Linked Open Data [54] approach has the advantage of offering a more expressive and interoperable data querying mechanism when compared to traditional databases. Linked Open Data assures that the stored information will be shareable, extensible, and easily re-useable. The Linked Open Data paradigm avoids the existence of information silos, which usually appear due to the lack of connections between datasets and the format incompatibilities. Once again cities will have to weight their requirements and choose between a more efficient approach using traditional SQL and a more interoperable and re-useable approach using SPARQL. From the security point of view, cities should also analyse the vulnerabilities of the semantic querying frameworks [55]. While solutions like Apache Shiro [56] and query sanitation can reduce some of the security risks, the security is less addressed in the semantic frameworks than in the traditional databases, mainly due to their lower popularity.

Finally, in the case of the Rule Engine, it can be configured to work in two different modes: the volatile mode or the persistent mode using the Apache Jena — TDB. As can be seen in Figs. 16 and 17 there are not notable differences in maximum used memory and maximum CPU allocation between both approaches, although the volatile mode used a bit more overall memory along the process. As can be seen in Fig. 18, the persistent mode is slightly faster than the volatile mode. This is due to the internal implementation of the Rule Engine, which uses temporal files, which results in slower read/write operations. Functionally the persistent mode is in one hand more robust, allowing for an easier system recovery and in the other more optimizable, as the new inferences knowledge is stored and reused, instead of having to infer it every time that the system is reset. Taking this into account, it is strongly recommended that the cities use the persistent method.

6.3. The Risk Analysis Model and dashboard predictions

Conditions such as MCI and frailty are characterized by gradual decline that may spread across years and be hardly noticed by seniors and their carers before the late stages, when the outcomes remain irrevocable [57,58]. Therefore, the clinical utility of forecasting is of substantial importance in order to avoid hospitalization and lessen the socio-economic cost of caring, while it may also significantly improve the quality of life of senior citizens. The risk analysis approach adopted in this work combines domain knowledge with machine learning techniques to derive health, well-being and lifestyle quantifying factors and metrics able to predict onset of MCI and frailty. To that end, time series are used to provide the statistical setting for describing the fluctuating heterogeneous data and projecting the data series into the future [59].

Time series forecasting is performed by using the well-established Box-Jenkins ARIMA forecasting method. Analysed data are collected by the Birmingham pilot, as they are currently the most complete, considering individual care recipient level, among all the pilot sites in the project. Each data series comprises monthly values of a specific factor of the geriatric model and a care recipient, starting from the beginning of monitoring period (January 2017) and ending with the final observation made in July 2018 (18 data points). Main characteristic of the acquired data is, though, a significant person-to-person and situational context-dependent variability, including seasonal patterns detected in the data of occasional subjects by now, and more are to be expected and handled by the analytics in the future (conveniently exploiting SARIMA variation). This summarizes the rationale for employing a quick straightforward extensible univariate forecasting method, robust to various underlying data distributions, integrated into the Dashboards. Other, and more complex, ML-based methods in City4Age Analytics are exploited for mainly data-driven recognition of features, new knowledge characterization and multivariate risk assessment from lower-level raw variables (LEAs, Measures), as elaborated in our relevant authored works [41,60]. The presented method of univariate assessment and prediction is transferable to similar problem settings, e.g. as currently applied in analysis and prediction of wider-scoped urban well-being level (with more factor variables and increased variations in the time series) in projects such as PULSE.¹⁹

Forecast accuracy is evaluated using forecasts starting from August 2017. Forecasting performances are calculated on two levels of aggregation, across all factors and groups and over the

¹⁹ PULSE (Participatory Urban Living for Sustainable Environments. Horizon 2020 Grant #727816), www.project-pulse.eu.

OVL only, and two forecast horizons, of 1 and 3 months. Bias metric, represented by the mean error, shows that forecasts for OVL had tendency to be lower than actual values (under-forecast) in the initial months, with improvement over time, reaching values close to zero (unbiased) in the final two months (June and July 2018). It has been observed that the forecasts with horizon of 3 months were slightly less accurate compared with forecasts with horizon of 1 month. In addition, average MAPE accuracy of forecasts with horizon of 3 months for OVL were lower compared to those over all factors. In general, all error metrics showed an inclination towards performance improvement over time, as more data points were used in the model training process. It seems promising that the forecasting accuracy will continue to improve as more data points are available.

The results obtained in the analysis demonstrate the generally satisfactory forecasting performance and therefore validate the overall usefulness of data-driven forecasting approach for assessing risk associated with specific geriatric domains and MCI and frailty in the presented setting.

6.4. Global discussion

Results and discussions carried out so far, obtained after almost two years of experimentation, allow us to re-evaluate the initial approach undertaken by the City4Age approach, also taking into account all technological improvements followed from the beginning of the project (December 2015).

Regarding the Personal Data Capturing System, the driving factor is unobtrusiveness. Since the beginning, one of the main pillars of the proposed solution was to put the smartphone at the centre of the sensing architecture, by exploiting its different communication interfaces (BLE, GPS, Wi-Fi, 4G) and its growing acceptance by elderly during their daily activities. Current pilot installations demonstrate that this approach is valid and produce good results in term of data throughput. However, with recent improvements in the field of 4G smartwatches, accompanied by a general decrease of their cost, the data collecting and forwarding task can be accomplished with a far more unobtrusive device, provided that its power autonomy is sufficient at least for the whole day.

In order to pursue a valuable Smart City perspective, data related to elderly behaviour on a home and/or City scope should be retrieved from already existing sensing infrastructure, rather than deploying several sensing networks, often not communicating each other. For this purpose, an open and facility managed BLE beacon infrastructure could be a valuable solution for the user indoor positioning in public spaces, like shops, pharmacies, supermarkets, etc. By publicly sharing beacons' IDs, user localization inside these places could be also easily shared, with the necessary privacy and security countermeasures. Analogous situation could be related to other services, like transportation and energy provision. Data related to the use of public transportation or power consumption inside buildings could be managed directly by service providers, which could also share them with final users and third parties, guaranteeing the proper privacy level.

Another critical factor of the proposed solution is the modality how collected data are sent to the Shared Repository. The field of application this solution has been thought for, i.e. the early detection of MCI and frailty conditions, does not have real-time constraints for data communication and analysis, therefore the preferable way should be the digest mode communication, where blocks of data are cumulatively sent at specified time intervals. This operating mode has the advantage of being faster than real-time communication, which, in turn, implies less power consumption for sensing devices.

Recalling the Smart City perspective, the most important data managed and generated by the whole system architecture must

be shared with third parties, in order to allow further elaboration, mainly for research purpose. To this end, the provision of SPARQL endpoints for data sharing should be enforced. Currently they suffer of higher latency with respect to SQL queries and relational database, but provided data are more shareable, extensible and easily reusable.

Finally, the last critical aspect of the proposed solution is the effectiveness of the Risk Analysis and Prediction Model. The factorization in the geriatric model reduces the complexity of monitored parameters, potential relations between behaviour variations and the number of scoped Measure variables, while still capturing the typical observed complex interdependencies, with all the Factors, Sub-factors, and other higher-level nodes being properly defined, maximally conditionally independent from each other. Assessing the effectiveness of the model still requires further months of experimentation, in order to consider a sufficient temporal horizon for the refinement of the algorithms and defining what is the best forecast horizon. Another point to evaluate over time is the adequacy of the set of Measures currently considered, verifying if they are comprehensive enough to correctly detect the actual behaviour of the elderly person, or useful enough for profiling care recipients.

7. Conclusions

This work presented a critical performance analysis of an IoT-aware AAL system for elderly monitoring. The analysis of the city-wide data capturing layer, i.e. the Personal Data Capturing System, showed that sensing device's unobtrusiveness and power autonomy are critical factors for setting up a sensing infrastructure able to collect data in a continuous and unbiased way. The Shared Repository, i.e. the Cloud-based centralized data management repository, offers its best performances when operating in digest mode, with a persistent mode rule engine; although SQL queries are generally faster than SPARQL queries, the Linked Open Data interface should be preferred when sharing data collected by the system to third parties. Finally, the Risk Analysis and Prediction Model based on the concepts of GES, GEF, GFG and OVL provides its best results with the ARIMA method with a forecast horizon of 1 month. Currently, this setup is the optimal one for the early detection of MCI and frailty conditions, which do not require real-time interventions.

Future works are mainly focused on searching for wristband devices or smartwatches able to implement the needed functionalities, providing at the same time a good power autonomy, and on further refining the risk prediction model, by analysing the upcoming new data and implementing semi-supervised learning that integrates the expert geriatric assessments on specific granular data as referent baseline labelled cases.

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Conflicts of interests

The authors declare that there is no conflict of interest regarding the publication of this article.

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