Context Modelling in Ambient Assisted Living: Trends and Lessons

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Abstract

The current Internet of Things (IoT) development involves Ambient Intelligence which ensures that IoT applications provide services that are sensitive, adaptive, autonomous and personalized to the users' needs. A key issue of this adaptivity is context modelling and reasoning. Multiple proposals in the literature have tackled this problem according to various techniques and perspectives. This chapter provides a review of context modelling approaches, with a focus on services offered in Ambient Assisted Living (AAL) systems for persons in need of care. We present the characteristics of contextual information, services offered by AAL systems, as well as context and reasoning models that have been used to implement them. A discussion highlights the trends emerging from the scientific literature to select the most appropriate model to implement AAL systems according to the collected data and the services provided.

Keywords

Ambient-Assisted Living, Context-awareness, Context Modelling, Ambient-Assisted Living services, Internet of Things.

Introduction

The Internet of Things (IoT) has emerged as a field offering multiple devices and applications that fulfil the Ambient Assisted Living (AAL) purpose [3]. The IoT is widely used to provide a broad range of services including home automation and user monitoring. AAL and IoT are closely intertwined; IoT offers means to achieve AAL goals.

Providing services based on IoT supposed to react to events that are triggered in the environment. It is then essential for applications to perceive, understand and analyse the surrounding, which implies to be context-aware. Context-aware systems achieve their purpose by automatically considering the context they operate in without the user's explicit intervention [1]. Such systems improve usability by adjusting their services to the users and increase their efficiency with results that fit the context of use. They therefore hold significant potential to provide for adaptable services in ever changing environments. AAL is a sub-discipline of context-aware systems which aims to improve the quality of life, especially for people experiencing difficulties in their everyday life. It particularly benefits from the adaptability of context-aware systems. In this chapter, we produce a literature review that focuses on AAL services that ensure health, autonomy and safety for people with special needs who desire to stay home, regardless of their age, physical and psychological conditions [2]. AAL systems need to be continually informed on the ongoing situation in order to counter risks, improve autonomy and cure, and so, without disturbing the inhabitants' habits. This implies that AAL systems are equipped with various sensors that collect information on the person with impairments evolving in his environment, and actuators that modify the environment to adequately interact with him or her. Context-aware systems, by essence, must perceive the world of the inhabitant they intend to assist and reason on these perceptions. They are composed of organs that perceive, transmit, reason and communicate with the external world and deliver appropriate solutions that arise through several steps.

The first step is performed by sensors that collect contextual information from the environment. There are several types of sensors and listing them quickly becomes irrelevant as new ones are continually being released in a rapidly growing market. To this day, no standard to represent data collected by sensors has been established, even from the same type of sensor. Often, values are graduated on different measurement units; On/Off information may be expressed by the binary code 0/1 and vice versa.

In the second step, the data sensors collected is transmitted through different networks. There are various protocols for this process, some use Bluetooth, other KNX or Zigbee, to name only a few. Gathering the various data coming from various sensors and protocols communication is not trivial and the use of middleware is recommended to tackle the convergence of context information. Among the frameworks that have appeared in recent years, CoCaMAAL presents a cloud-oriented middleware approach [4]. Its aim is to provide a unified way to generate context information and to send it to the cloud. A multi-agent approach has also been proposed where each sensor is monitored by an agent [5]. An agent is composed of a three-level architecture: the sensor, at the first level, communicates with its proprietary protocol to the second level, named sink. The sink is responsible for the generation of data-stream that it then sends to the third level, the gateway. The gateway receives streams from all sinks and regroups all the agents. Other types of middleware can be found in the literature [6–9].

In the third step, the context-aware system reasons to elaborate actions that the actuators will carry out. Reasoning techniques, for the most part, are based on artificial intelligence to cope with constantly changing environments. On the one hand, this needs to represent information that is dynamic, heterogeneous and sometimes inaccurate, on the other hand, to adapt reasonings. Those are broadly classified into knowledge-based, data-driven, and hybrid approaches. Each presupposes specific data modelling to perform the reasoning.

Finally, actions on the world are executed by actuators. Like sensors, the types of these devices have rapidly expanded regarding the effects, either visual, oral or under multiple modes, and the protocol they used. Context aware systems must consider their impact on the environment and the inhabitant's reactions. This retroaction evaluation is part of the awareness of these systems. Creating new sensors and actuators, organizing them into various networks that allow for the establishment of complex and powerful data frameworks form the core of IoT research. For this chapter, we go one step further and examine how the data from the IoT can be used to build context-aware systems oriented towards AAL.

Several valuable surveys have been conducted on context aware systems, IoT and AAL. Some focus on computational aspects while others concern services offered. The survey conducted by [10] develops context representations, carried out by database and ontology modelling, and reasoning used to deal with the nature of context information. Reasoning is discussed according to the choice of sources, types of data and uncertainty of information. As well as [10], the surveys conducted by [11] and [12] examine various models of representation, opening on architectures and AAL platforms. Criteria on interoperability, scalability, confidentiality, security and fault tolerance underlie the comparisons. [13] include a discussion on situations where the models are applicable with respect to the nature of data and the types of sensors. [14] review services offered by context aware systems in smart homes and discusses the technical means, such as devices, protocols and algorithms, used to reason on context data. A more specific review focus on AAL services, presenting tools, technologies and algorithms, as well as the applications in monitoring, the prevention of wandering and cognitive orthotics devices [2].

The goal of this chapter is to review recent context models in order to determine the most appropriate context modelling and reasoning approaches to consider for implementing specific AAL services based on IoT. Surveys conducted on the field tend to isolate services from context models. However, the type of service delivered may constrain not only the type of data collected by the IoT technology but also how these are represented and the type of reasoning. It is then important to build a bridge between AAL services and context models. We suggest that the choice of model and reasoning depends on the type of service delivered. To achieve this goal, we will present a review on context aware systems for AAL covering the last decade (2010-2020) to identify last development trends. In this review, services, contextual representation and reasoning are described and relations are established between them.

The chapter is organized as follow. An overview of the most frequently offered services in the AAL is presented in the first section. In the second section are presented the data used according to the context. The third section overviews the context models and reasoning that have been used during the last decade. In this section, we present each model extensively and give a detailed view of context modelling and reasoning developed to provide services. Doing this enables us to synthesize and derive trends in the discussion section before concluding the chapter. A glossary can be found at the end to resume all the abbreviations used in the paper.

Ambient-Assisted Living Services

To address the impacts of the services choice on context representations and reasonings, we first define what is a service, and more specifically an AAL service. We then present the services according to the beneficiaries, first the inhabitants and second the caregivers. We close this section by presenting the basic services that are needed to achieve the previous ones.

Definition of AAL services

[15] distinguish care and assistance services on the one hand, and software services on the other hand. The latter are defined in information technology as a set of functionalities performing actions. The focus is put on data, processing, control flow, and interoperability between all the components. The former derived from a business and customer perspective and are defined in terms of added value provided to customers. In this section, we adopt the perspective from the customer to present the various services related to AAL, where the customers are the beneficiaries of AAL, either inhabitants or caregivers.

AAL services for people with special needs are by nature medical and social. They shift the focus to helping frail people in their daily life, to compensate for the natural reduction in physical or cognitive capacities they encounter. The task to assist becomes then central, instead of the technology used to perform it.

It requires generally a collaboration between different actors and a user-centred approach to achieve the appropriate service that fulfil the collaborative assisted living ecosystem. Thus, an AAL service refers to a composite service or a set of services that combines several simpler services to meet customer needs. It usually aims to achieve some of these goals:

- Aid persons with specific needs in their activities of daily living (ADLs).
- Promote autonomy and social integration.
- Personalize assistance according to capacities, preferences and habits.
- Adapt the assistance according to the evolution of the persons.
- Integrate needs of caregivers to help providing care and reduce burden.
- Enhance coordination of care through efficient systems.

AAL services have been widely explored in ambient intelligence field, where technology is integrated seamlessly into everyday objects to empower people through sensitive and adaptive environments. Among the variety of AAL services offered, we mainly focus in this review on services delivered indoor as shown in Figure 1. Outdoor assistance is covered in detail in the smart city literature. The indoor environment is generally restricted to smart homes [16, 17], but nursing homes and hospitals are also considered [18].

Services for inhabitants

AAL services are dedicated generally to a wide set of inhabitants, most often elderly or frail people. For instance, [19] describes AAL services as providing intelligent and context aware assistance for elderly people at home. [20] states that most of AAL services are dedicated to seniors and people with special needs, disabilities or impairments. This is shared by [21] that points out the capacity of AAL services to assist frail persons anytime and anywhere in their ADLs. But some services are dedicated for more specific categories of inhabitants including persons with loss of mobility [22], persons suffering from Alzheimer's disease [23] and other cognitive disabilities [4, 24], persons experiencing a loss of perception or with chronical disease such as diabetics [25, 26].

There is a consensus among AAL designers that the off-the-shelf devices do not suit the inhabitant's needs and preferences. An adapted and personalized service is required to help inhabitants to stay home by assistive services, alert services and home automation.

Fostering autonomy is a major goal pursued by ambient assistance for inhabitants. Also called cognitive assistance when used to compensate cognitive deficits, the ambient assistance delivers appropriate prompts when the inhabitant forgets to carry out an ADL [27] or fails in performing it [16, 23, 24, 28]. Verbal and oral prompts are displayed to complete basic ADLs [16, 23], specific ADL such as taking medicine [26, 29] or more complex one, such as cooking [24]. Promptings are displayed in the smart home, on smart phones [30, 31] and through conversational agents [29, 32]. Some actions may even be physically carried out when the AAL system turns off electrical appliances [24, 30] or moves objects with robots [33].

In case of emergency, either due to abnormal physiological situation, lack of movements and abnormal body posture, AAL services alert the inhabitant or inform caregivers to resolve the situation [34]. In this case, it is important to quickly reach the inhabitant at the right moment in the right place [17, 31]. Feedback is also crucial to engage an efficient conversation between the inhabitant, AAL service and eventually caregivers to evaluate the dangerousness level [35].

Recent years have also seen the explosion of home automation services. Energy saving and lighting automation are often the targeted functionalities [3, 28]. The key principle is to personalize the service according to the on-going activity [36], the time of the day [23] and the inhabitant's perceptual capacities and preferences [28, 37].

Services for caregiver

Caregivers benefit from AAL services, which helps monitoring health, coordinating services and reducing burden. We use the term caregiver in a broad sense, meaning everyone who is giving care, including medical personnel and relatives with no medical training.

Relatives, also called informal caregivers, are often loved ones or neighbours, generally not living with the inhabitant. Few articles tackle the issue of an inhabitant living with his caregiver [38]. The area of expertise of the relatives is usually unknown and is not taken in account when deploying general services. Services dedicated for informal caregivers are aimed to reassure caregivers, alleviate the burden and help them prevent adverse situations [23].

Medical personnel, also called formal caregivers, are usually but not only, nurses, beneficiary attendants, psychologists, occupational therapists and doctors. It is easier to define their expertise. Therefore, the language of interaction reflects the proper professional terms. In the hospital and in the nursing homes, the aim is to alert medical personnel as soon as a hazardous situation occurs [18, 39]. When the inhabitant lives at home, healthcare providers may be alerted remotely to intervene in case of fall, fire risks and vital signs monitoring [30, 34, 35].

Recommendation systems are part of medical services to help making the right decision based on objective data coming from medical history, physiological and environmental sensors [5, 40]. Finally, coordination of the interventions between the multiple healthcare providers constitutes a service that requires context-data [25].

Basic Services

Basic services are prerequisite for the elaborated services dedicated to inhabitants and caregivers that we have presented previously. They are intended to recognize what is going on in the smart home, either to identify the inhabitant's behaviour or to predict his next behaviour. Basic services concern mainly activity, body posture, location and identification of people.

Activity recognition

Activity recognition is a popular service and literature on this topic is abundant [29, 30, 41]. Activities are generally identified by a sequence of actions that may be sequential and a set of events occurring in the smart home. Context is helpful as most people reproduce habits leading to actions repetition in the same order, at the same moment and the same place. Most often, authors discriminate activities among various ones from three [42] to five [43]. Activity recognition may occur in specific area of the smart home, like kitchen and bathroom [44].

The activity recognition helps diagnosing abnormal behaviours [3, 45], detecting change in the habits [4, 46] and predicting the next activity the inhabitant may perform[16].

Posture recognition

Posture recognition consist most often to discriminate among three positions lying, sitting and standing. Associated with activity, it increases the likelihood of activity recognition [3, 27]. Posture recognition is intensively used to identify fall. A fall is detected when the posture changes abruptly from sitting or standing to lying at an unconventional place [27, 39].

Localization

Localization services aim to determine where persons or objects are within a given environment [47, 48]. While this service can be useful when someone gets lost, it is commonly used as a context information for other services, such as activity recognition or posture recognition.

A navigation service helps reaching a given destination. It combines a localization service with a cognitive assistance. This service usually involves a prediction of the next paths the inhabitant will follow to reach his goal [49]. The concept of destination is also extended to include completion of various tasks, as required by planification [31, 50].

Predictive services

Even if predictive services are most often included in other basic services, some papers focus specifically on how to determine the next item, either activity, behaviour, medical status or room. They analyse the past and current situation to infer what might occur next.

Predicting next activities is part of some AAL services to determine the most likely activity to assist in future [16]. Also, predicting the next place to go is the core of navigation services [48]. Prevention is by essence a predictive service, whose purpose is to avoid any dangerous situation, both medically and in the daily living [34]. In recent years, researchers pushed predictive services into the realm of psychological predictions. In [4, 51], the authors aim to detect long term changes, predicting then future behaviours, future psychological states or future disease symptoms. This prediction relies heavily on context data as no sensor can measure directly a psychological state.

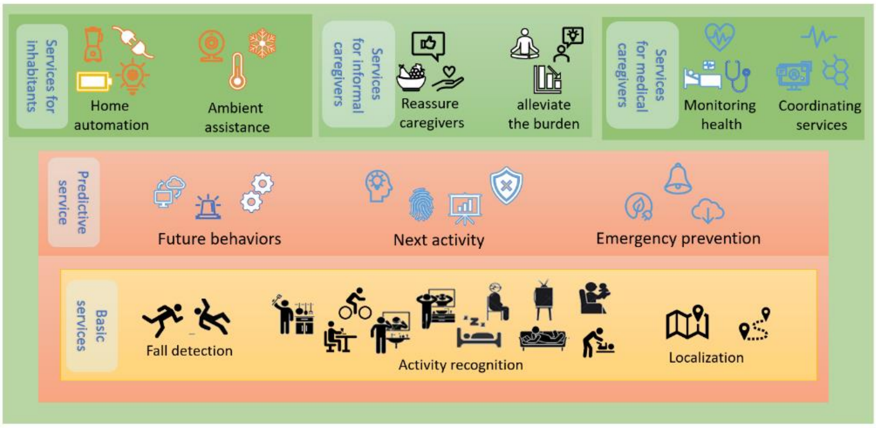

Figure 1: Indoor Ambient Assisted Living Services.

In this section, we presented a review of current services offered in a healthcare context. We have presented them as being independent services. However, many papers in the literature propose solutions that include more than one service. For instance, COOK [24] is a cooking assistant coupled with an autonomous security service for cooking. It combines a cognitive assistant, an emergency prediction service relying on a localization service for some safety rules.

Context information and context-awareness in AAL Systems

Understanding and defining the context is a prerequisite to its modelling. This section will describe sources and characteristics of context, context-awareness and will emphasize its importance in AAL. We will present how the main challenges of context modelling derived from the nature of context information, which is dynamic, heterogeneous and sometimes inaccurate.

Context is a concept used in several domains to generally describe all the information or circumstances related to a fact or an event and that can help to explain or understand it (definition adapted from the Oxford dictionary). For instance, in the field of education, the concept of learning context is centred toward a human and its learning resources: it is the "various circumstances in which learning might occur, where the learning context consists of students, culture, teachers, lesson plans, etc. In addition, learning context refers to the set of learning activities, including the space in which learning itself occurs, and students' perceptions of the ability of a particular space in providing rich learning experiences" [52]. In fact, some authors such as Bazire and Brézillon [53] found in the literature hundreds of definitions of the concept of context. Therefore, it is prerequisite to define the concept of context and context-aware computing applied to AAL systems for choosing the appropriate model.

In computer science and more specifically in ubiquitous computing, the Anind K. Dey definition of context is probably the most widely shared: "Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves." [9] The same author added that "a system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task" [9]. Related to ambient systems, context-aware computing "describes the ability of the computer to sense and act upon information about its environment, such as location, time, temperature or user identity. This information can be used to enable selective responses such as triggering alarms or retrieving information relevant to the task at hand" [54]. From those three definitions, we can extract some findings:

The nature of information for describing a context is task dependent. In fact, the entity (user or system) tasks are central to the notion of context

If we compared the context to a "space", the user, and more specifically the system/object with which the user is interacting to perform a task is at the centre of this space.

Information about the context (i.e. contextual information) can be divided in four categories: (i) information about the users; (ii) information about the environment/space surrounding the users; (iii) information about the spatial elements of that space; (iv) information about time or temporal link between contextual information.

Based on these definitions and findings, we will, in the next lines, present and discuss about the concept of context and contextual information in AAL (Figure 2).

Contextual information on inhabitants

Information about the users is part of contextual information. In AAL, final users who benefit from services include inhabitants as well as caregivers. We first focus on services for inhabitants. To deliver adequate information under suitable forms for assisting, alerting or preventing, necessitates to know the capacities of the user to handle such information. Any contextual data regarding the user concern and ability to deal with the service when it is delivered is also relevant. We then divide the contextual information on inhabitants in two categories that correspond to the static and dynamic characteristics pointed out by [3]. The first category regards general information, including capacities and preference. This information is rather static or evolves slowly over time. The second information, dynamic in nature, regards the current situation of the inhabitant, especially his position or physiological data.

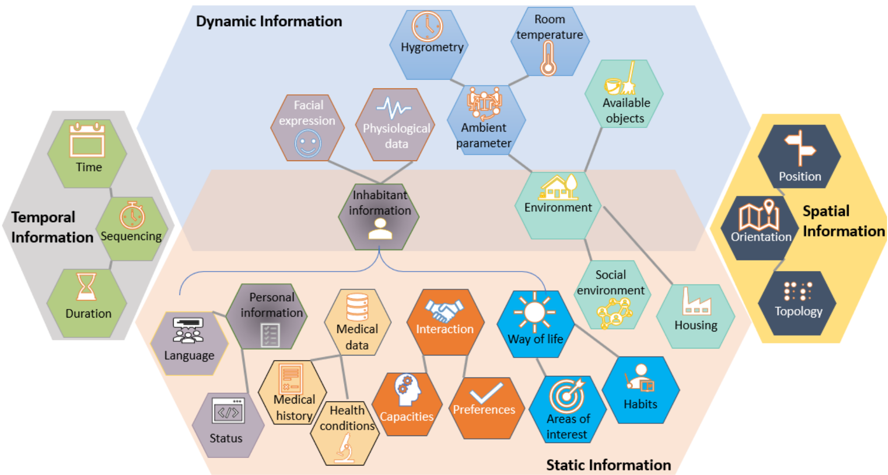

Figure 2. Contextual information for AAL services

Static information on inhabitants

First, information of the status help identifying the inhabitant who will receive the service. Even if the status information is not always explicit, many authors determine name, age, gender, language as important information to hold [3, 27, 30, 51]. This information may be part of the medical history, some authors refer globally.

Second, as this literature review focuses on assistance, great emphasis is put on medical data such as diseases and symptoms. Some authors identify specific disease or health conditions, such as diabetes, pregnancy, diet, motor or cognitive diseases [25, 26, 29]. Most prefer to refer to a broad description of diseases they include in the medical history without specifying them. Especially they mention chronic diseases, medication and physiological data such as hypertension. Also, weight and size are indicators of health [51]. Some authors identify the medical model they rely on, either the international classification OMS [26] or a more local classification, hold by a shared medical record [18, 51, 55].

Third, some authors pay attention on how the service will be delivered. Besides the language, the interaction is determined by the sensorial capacities, for instance failing-eyesight [31, 56] and the preference such as the gender of the system voice [57]. The inhabitant profile is also determined by health conditions, such as head trauma that limits the number of stimuli [18]. Also, acceptation of messages is considered [57].

Fourth, the habits and areas of interest are taken in account, such as preferences in food or movies [29, 51]. Such habits may have an impact on health, such as smoking [55].

Finally, ethics consideration is part of the context due to the sensitive data handled. For instance, the level of confidentiality of the service delivered is determined by the situation and the persons who could be aware of the collected data [39].

Dynamic information on inhabitants

Delivering appropriate services needs to collect contextual data that allows to judge the severity of the situation. Plethora of vital signs are gathered to evaluate at each moment the health status. It includes heart rate, respiration rate, blood pressure, blood oxygen saturation, blood sugar level and body temperature [3, 18, 26, 27, 34, 51, 58]. It is gathered continuously through wearable devices or at specific moments with electronic devices such as finger pulse oximeter and blood sugar meter.

Recognizing emotion and facial expressions provide information on the pain felt and the confidence in the service [29, 57].

The location of the inhabitant and his position in space is also an important source of contextual data. It helps determine the service and its modality of delivering. Fire emergencies exemplifies how the position data influences the service: Where (In which room the message must be sent?); When (Waiting for people coming back to the kitchen?); How (On the closer screen or by oral message?) and What (Is the inhabitant not reachable requiring to turn off the stove automatically?) [24, 35]. Information on space and the influence of the position of the inhabitant will be more detailed in the section Spatial information.

Environmental information

Environmental information is by nature contextual. It concerns everything that surrounds a person. In the International Classification of Functioning (ICF) model validated by the World Health Organization, the environment is a key component to explain the human being functioning [59]. Individuals characterized by their deficiencies and capacities interact with the environment to carry out activities. This interaction generates handicap if the individual with his capacities is unable to complete the desired activity in the specific environment. Among the physical, social and financial environmental aspects involved in ICF, context in AAL retains just the first two. Physical environment refers to all objects and physical structures that the person may be in contact with during his life. For the purpose of AAL we restrict this physical environment to home. Social environment refers to the persons who surround the inhabitant and the ones he could meet to satisfy his goals and fulfil his activities. In both social and physical environment static and dynamic features of the collected data are distinguished. We first present the data gathered to determine the physical environment; and second the data to determine the social environment.

Physical Environmental Information

Physical environmental data describe on one hand how the inhabitant feels comfortable and on the other hand how he interacts with the environment to complete activities. The first set draws together data regarding ambient parameters [37, 40, 60]. Among multiple parameters some papers mention at least lightness [3, 28, 51], noise [34, 44, 51], temperature [17, 30], humidity [17, 60], carbonic gas and smoke concentrations [32, 60]. The second set of data helps describing the current activity in process. Knowing the room where the inhabitant is or the seat he is sitting on, points toward the activities to recognize. It supposes to locate the inhabitant and know the layout of space and furniture. Spatial reasoning will be described in the section Spatial information. We focus here on contextual data collected to help determining activities in progress. Spatial data are collected through infrared sensors, pression mats and contact on doors to locate the inhabitant. As almost all studies use such sensors, let name just few [18, 23, 36, 43, 61, 62]. Some studies use specific information to determine the kind of activities in process as electrical power [35–37, 43, 60] or flow sensor [43]. Moreover, some activities are precisely targeted when a specific object is involved during its execution such as dry soil to water plant [32], phone when calling [57] and all Radio Frequency IDentification (RFID) sensors placed on objects [26, 63]. Even more precisely, RGB-D (Red Green Blue-Depth) cameras inform about movements done by the inhabitant for recognizing current activities [39, 63–65]. Wearable sensors are generally used to collect physiological data, but accelerometer gives relevant information about the activity in process or the severity of the situation. It is the case when the inhabitant is falling [27, 34, 43, 63]. Finally, some authors pay attention to the state of the objects involved in the environment to ensure that they are available, such as battery level [60] and computer state [30].

Social environment

Finally, the social environment is taken in account. It implies registering in the medical history the name and function of medical staff [25] and in general, information on relatives [3, 25, 48, 51]. This information is necessary when caregivers need to be reached, either for informing of the evolution of the inhabitant's daily life or to alert when adverse events occur [36].

Temporal Information

On one hand, some context-aware systems are reacting to specific information at a specific time without any notions of historic or temporal logic. On the other hand, AAL services need, in most of the case, an history of the contextual information in order to adapted services or recognize series of human activities. For instance, knowing how much time a day a user is using the oven, or if the oven was started before detecting someone in the shower. Such information is the premise of activity recognition.

Temporal information is essential to support activity recognition and error detection. Especially, determining if activities are executed in parallel or sequentially may lead to diverse inferences. It is then required to keep a trace of the time a contextual information has been collected. For that purpose, Allen [66] proposed a framework to support the Temporal reasoning using the Interval Logic. His work is one of the cornerstones of the activity recognition. Since the work of Allen, the W3C proposed a draft recommendation for a definition of an OWL ontology to specify the time and the temporal relation between concepts [67]. It provides a framework for the use of the temporal concepts in ontologies that describe context, such as the model described in the next section.

Other projects propose to use Machine Learning (ML) approaches to manage temporal relation and, for instance, classify series of events into activities and thus generate higher level of contextual information, either decision trees [58], dynamic time warping [68], Support Vector Machine (SVM) [58, 64], Bayesian networks (BNs) [16, 49], specialized probabilistic models such as Markov models (MMs) [36, 38, 51] or sequence mining [16, 50]. In [69], the authors are using a hybrid approach by extracting frequent episodes of events with the APriori algorithm and using an MM to model the transition between the user's activities.

Spatial information

Spatial information includes the structure of environment itself (i.e. the topology) and the position of the objects or users in the space. Combined with other contextual information, the movement of specific objects monitored over time helps inferring the activities the user is performing [41, 47]. It is required then at some extent to describe the space and its topology and know the positions of the entities (i.e. objects or users) in a Euclidean space.

Geometrical systems are used to describe spatial information. In [70], an ontology model includes a referential system where each physical entity received a three-dimension cardinal position and a time stamp related to the last position when a user or an object was located. In [71], the authors extend the ontology model of [70] to describe an environment's topology. They include zones delimited by walls, cabinets and doors. Zones are described by a list of 2D positions, forming 2D geometrical structures, and entities (objects or users) are placed into zones. Finally, the users' field of view is also represented to determine which entities the user may perceive. This spatial information, added to other contextual information, allows reasoning over service provision on the most adapted devices for a specific user.

Most of the works use descriptive representations to reason on space, either using ontologies [7, 17] among other knowledge representations [49].

Delimiting the context

One of the problems that comes up regularly in the literature about context is to delimit its spatial and temporal boundaries. The definition proposed by [9], as the capacity for a computing system to perceive contextual information, does not stand anymore for distributed systems and IoT. In fact, context boundaries are constantly pushed by aggregating information for different nodes such as smart phones, sensor networks, etc. The context boundaries, instead of being delimited by the capacities of perception, may be defined by the goals of services offered. For instance, the context of cooking assistance [35] may be restricted to the preparation of meals, such as the culinary fence, the state of the meal in preparation and the state of the oven. However, in several systems that propose a framework for multiple services

[16, 23], the context boundaries must then be extended until the upper one. But with web services, the boundaries need to be pushed even farther. Thus, the limits of context at the end must be ultimately specified by the developers and the different end-users.

Heterogeneity of data

The heterogeneity of the sensors that are producing data at different rhythms and in different formats raise the issue of context-aware standard. In one of the first context-aware system framework, the Context Toolkit [9], widgets are filtering and transforming data before sharing it to other services. In modern IoT sensor networks, such transformation can be performed directly in the nodes. However, in most AAL systems that implement context-awareness, a certain level of context modelling is required to allow higher level reasoning and inferences. In the next section, we are covering different approaches in modelling contextual information for AAL systems.

Approaches of context modelling in AAL Systems

As discussed in the preceding section, context is a complex but key aspect for AAL systems to provide adaptability to users' needs. This section focuses on studies that provide precise information on how authors approach context modelling and reasoning in their AAL systems. However, it is important to note that multiple studies in the literature do not explicit those concepts despite discussing context awareness [48] or support systems for AAL services [19, 38, 64, 65] . Hence, we could not include them inside our analysis. We describe several works done in the literature, focusing on their approaches of context modelling and reasoning. Approaches developed so far are either knowledge-based, a model is provided, holding semantical knowledge; or data-driven, data is the main source of reasoning; or sometimes both, what we will refer to as "hybrid approaches".

Knowledge-based approaches

Recent literature promotes logic-based and semantic models, where explicit description of domain knowledge and inference engines are used to derive implicit knowledge. Advantages of knowledge-based approaches include a shared understanding of data and their semantics, as well as reasoning mechanisms. Some of the recent works in this vein are summarized in the following.

Multiple works are dedicated to software architecture.

In 2010, [5] describes an architecture for IoT based on a multi-agent approach. The architecture handles low-level data-stream of sensors and translates them into higher-level data, giving them a healthcare-related semantic, thanks to specialized ontologies and inference rules.

SAMURAI [7] is another architecture designed to tackle large-scale knowledge-based context. It relies on a semantic representation of the rooms and activities in OWL. Batch reasoning is performed using Apache Spark and simple RDF triples as rules. Complex event streams are handled by Esper and help provide higher-level interpretation of low-level events. Finally, GeoSPARQL's spatiotemporal reasoning data is used as an input for classification and clustering, opening the way to activity recognition.

The work in [33] describes a multi-agent robotic intelligence for user assistance in activities like moving objects. An event model is represented in an ontology when a SQL Database stores agent's memory. Ontological reasoning is then performed to recognize the current situation, followed by the simulation of assistance in a virtual environment to ensure the feasibility of actions before doing them in the real world.

Finally, in 2018, [18] describes a cascading framework for healthcare support in hospitals and nursing homes. The framework rests on an ontology compiling medical domain and IoT knowledge to semantically annotate observations inside the environment. After filtering and aggregation, reasoning is performed on the observations locally and in the cloud using OWL 2 RL or DL and the medical staff is prevented in case of emergency.

Medical staff can also benefit from recommendations to support their decisions especially using ontologies for contextual handling and rule-based inference.

In 2012, [25] proposes a tool to ease the coordination of professionals working with chronically ill patients. An OWL-DL ontology of the chronical illness domain has been built considering 19 diseases, 2 syndromes and 5 social issues specificities and adequate interventions. A personalized ontology is then built according to the patient diagnoses and symptoms and probabilities of illness and effective interventions are computed based on the ontological properties and relations.

[26] is a recommendation expert-system for anti-diabetic drugs selection built on top of an ontology (medicine name, composition and associated information) and a diabetic patient tests ontology in OWL with Protégé. Medical guidelines were used as criteria for SWRL rules about drugs selection, which were then converted to JESS for reasoning. Recommendations are inferred by applying the rules to the patient tests data, resulting in a list of recommended drugs and their descriptions.

On the patients' side, multiple instances of AAL systems are described.

COOK [24, 35] is a cognitive orthosis designed to help people with head trauma injury during meal preparation. The orthosis relies on an OWL ontology holding concepts such as home space, devices, assistance and activities. Data gathered from the sensors is fed to a "Preventive Assistance System" following Hierarchical Task Network-inspired scenarios to detect hazardous situations, to alert the user and the caregiver, and to stop the stove in case of emergency.

[3] presentes E-care@Home, an adapted house for older adults with special needs, that can offer domestic automation and health e-monitoring (anomaly detection and emergency) based on activity recognition. In E-care@Home, context raw data streams from various environmental and body sensors are collected and stored into a database that feeds an ontology of sensors belonging to an ontology network that also contains ontologies on events, situations, time intervals and the physical environment. Activity recognition is then performed by a set of logic rules built on top of ontologies and non-monotonic reasoning using Answer Set Programming for stream reasoning.

[40] proposes Dem@Home, an ambient intelligence system for clinical support of people living with dementia. Ambient and wearable sensors observations and application domain specifics are captured in an OWL2 ontology that is aligned on DUL and integrates OWL Time1 to capture temporal context. OWL2 reasoning enables activity recognition while SPARQL rules are used to determine non-pharmaceutical interventions to improve care and to extract clinical problems.

[28] proposes a home automation system that supports personalization for elderly persons and their caregivers. They use an ontology for devices and digital personality representation. The ontology integrates OWL Time for temporal

1 https://www.w3.org/TR/owl-time/

aspects. Rules are added to determine automatic actions to perform and to check autonomously whether the intended actions are performed correctly.

Moreover, AAL solutions often rely on activity or situation recognition.

In [42] where raw data from pressure, contact and ultrasonic sensors are described in CoSSN (Cognitive SSN), an ontology that supports semantic detection of three activities (Dressing up, watching TV, taking shower) by the means of SPARQL rules and queries.

[61] provides some strong insights on how they use an ontology combined with a reasoner to perform real-time activity recognition despite focusing on time-window manipulation. The OWL-DL ontology holds representations of activities of daily living, house and sensors. Using Pellet and their described algorithm they achieve real-time activity recognition with high accuracy.

[43] presents an ontology-based activity and body posture recognition for older adults with cognitive and physical impairments. An ontology is used to store data from wearable sensors, objects used, and actions performed by users. OWL reasoning with Hermit reasoner enables to derive users' activities (cooking, having meal, taking medicine, washing dishes, watching TV, wandering in lounge, toileting) and body posture (standing, sitting, walking).

[17] proposes an ontology-based situation aware assistance for cognitively impaired people in smart homes. OWL reasoning using SPARQL is used for situation recognition (e.g. sleeping, making coffee, cooking, drinking, watching TV, location, events) and user prompting.

Finally, for the recognition of complex kitchen and bathroom activities of aging population in an AAL environment, [44] uses an ADL ontology enriched with rules to derive events from raw data of multiple sensors first, and then activities from events.

Navigation and location are other topics discussed in the literature.

[72] aims at minimizing the need in sensors by inferring the user's location and intention from their control logs, i.e. how they interact with the system and not with the environment. To do so, an ontology is built describing the user, devices, basic services, locations, effects and the AAL system itself. Relations link the user with doors, rooms, devices, services and their effect. SWRL rules are then used to infer the movement of the user, its intention and suggest adequate device or service activation.

[48] presents one of the very few outdoor services considered in this review is the assistive navigation system based on augmented reality for people with MCI. The system generates navigation based on the user's cognitive context (orientation needs) and well-known places to supply spatial orientation and cognitive facilitation. The user's context is represented by fuzzy sets that enable to dynamically generate routes due to the use of fuzzy logic.

Finally, some works cannot be labelled behind the previous categories.

Recently, Converness, a conversational assistance system that analyses verbal and nonverbal observations and provides speech-based information about basic care (e.g. injury treatment) to older adults with cognitive impairments (Mild Cognitive

Impairment (MCI), dementia) was proposed in [29]. Converness makes use of OWL2 ontologies to model sensor data, user profile (e.g. medical data, preferences), nonverbal data (e.g. gestures, facial expression), and conversations themes and topics. OWL2 reasoning and SPIN/SHACL rules are then used for topic understanding and conversational awareness when defeasible reasoning (non-monotonic rules) is used for user-centred conflict resolution (context disambiguation).

Concerning the management of a smart building, a comfort-compliant energy saving system is proposed in [60]. This work uses an OWL ontology to represent the smart building concepts, environmental parameters and devices, while rule-based agents and defeasible logics are used to enforce energy saving policies in the automatic management of the smart infrastructure.

The works presented here show the importance of the integration of semantics in AAL systems. In fact, semantics provides a better understanding of the meaning of data collected by IoT devices and favours human and machine readability and easy interpretability. For example, [26], E-care@Home [3], conversness [29], COOK [24, 35] go beyond sensors raw data and provide high level descriptions of environments, users' needs and profiles, activities and their preconditions aligned with changes captured in raw data to provide health or safety assistance to users with special needs. However, capturing semantics requires a good understanding of the domain and procedures, a good trade-off between the expressivity of the chosen knowledge representation formalism and efficiency of reasoning, and ideally a good mean to describe and reason on temporal relations between data or activities as in [3] and [28]. In some cases, inaccurate or missing sensors readings, the availability of huge volume of data and the need for prediction of future behaviours can be hardly manage with knowledge-based techniques: here come into play data-driven approaches.

Data-driven approaches

Data-driven approaches use statistical and ML techniques on context datasets. The best strengths of these models are their independence from precise human description of knowledge and their ability to handle noise, uncertainty, or incomplete sensor data. They have been widely used for some service provision in AAL systems.

A lot of works focuses on activity or posture recognition as a baseline.

[62] takes a brain-inspired approach for human activity recognition. Starting from the sensor values, a network of "neuro-symbolic" network, similar to a Neural Network (NN), is trained with online-available dataset. Additional knowledge and reasoning variables from external sources are supported such as time, or presence. The current activity is then deducted by inputting the current situation to the network.

SCAN [63] is a framework for activity recognition which relies on three layers: recognizing artefacts with which the user interacts, inferring the user's activity and representing the user's activity. First, acquired data is compared to a threshold to extract the interactions between the user and his artefacts. Then, activity inference is performed by matching the duration, number of beats and artefacts with hard-coded criteria.

[58] propose a generic feature engineering approach. From a variety of wearable sensors, robust features are selected to generate reliable classification models for activity recognition. The aim is to reduce the costs by facilitating execution of algorithms on devices with limited resources and by using as few sensors as possible. In this study, SVM, Random Forest and Extremely Randomized Trees (ERT) show better accuracy for all combinations of sensors among six classifiers.

[64] presents novel methods and ideas to design automatic posture recognition systems using an RGB-D camera. Two supervised methods are introduced to learn and recognize human postures. The first method consists in training CNNs based on convolutional features extracted from 2D images to recognize human postures using transfer learning on RGB and depth images. The second method consists to model the posture using the body joint configuration in the 3D space and recognize posture through SVM classification of 3D skeleton-based features.

[65] presents an activity recognition system based on skeleton data extracted from a depth camera that can be installed in an AAL environment. The system makes use of ML techniques to classify the actions that are described with a set of a few basic postures known as "key poses". The training phase creates several models related to the number of clustered postures by means of a multiclass SVM, trained with Sequential Minimal Optimization (SMO). The classification phase adopts the X-means algorithm to find the optimal number of clusters dynamically for activity recognition.

Going further, some works tackle prediction or behaviour trends that may arise.

[16] with MavHome project, aims "to create a home that acts as an intelligent agent" detecting actions of its inhabitants, predicting the next action and acting accordingly to assist [50]. Interactions between inhabitants and devices are stored inside a Markov chain of events, hence the next action is the action with the highest probability considering the current state and precedent known sequence of actions.

[22] presents an AAL system that uses spatial and temporal context to recognize ADL and detect increasing or decreasing health conditions of elderly with diabetes and decreased mobility. Privacy compliant low-resolution visual sensors data feeds a Hidden Markov Model (HMM) with k-Nearest Neighbours (k-NN) classifier for user's location. Mobility patterns and sleep duration estimates serve as the backbone of ADL recognition and problem detection.

To detect future anomalous behaviours of elderly suffering from dementia, [74] makes use of low-level wireless sensors (motion and door entry point) in an existing home, making it smart. The collected sensor observations are then represented either in time series or start time/duration parameters to enable an RNN to predict the future values of activities for each sensor and then, the future behaviours of the resident.

[32] designed a virtual butler which provides spatialized vocal interaction to the inhabitants. The state of all sensors within the home is stored inside a buffer and updated with new records to feed ML classification algorithm. Classification rules derived from a pre-trained multilayer perceptron neural network are used to predict whether a situation is normal or abnormal and to interact with the inhabitant accordingly.

Privacy is another important issue represented.

[69] present a pattern mining approach that do not necessarily involve highly intrusive sensors. Heterogenous sensor data are mined to detect frequent patterns and activity recognition can then be deduced from the chain of events that is detected by the system.

Following this privacy trend, [39] proposes an intelligent risk detection and telecare assistant with a focus on privacy protection for long-term care of elderly or disabled people. The video-based system gives the opportunity to caregivers to assess the real risk and system interventions by visualizing the scene and the user at different levels of privacy including raw image, blur, silhouette or 3D avatar. The video stream is processed with Gaussian Mixture Model (GMM) and Multi-cue background subtraction (MCBS) for object detection (e.g. faces, bodies) and situation recognition (events and activities).

Finally, some works deal with other concerns such as positioning or multi-occupancy.

Since many AAL services are based on location of objects of interest [73] proposes a position-based AAL framework that combines a device-free localization system based on Radio Tomographic Imaging (RTI) and an ADL monitoring system together, for ageing in place. In the monitoring system, the position-based marks offer the emergent representation of daily activities and are used with a Convolutional Neural Network (CNN) to accomplish the tasks of recognizing ADLs and detecting anomalies.

[38] explore the problem of multi-occupant context modelling through their data traces disambiguation. First, an accessibility graph of the binary sensors network is built. Then, sensor data is aggregated into user traces and used to train MMs of multiple occupants. Parameters are obtained by following a Conditional Least Squares method combined with a distance-based assumption.

These approaches are very efficient for pattern recognition and prediction problems where some models are trained on raw data collected from various IoT devices to recognize actions/behaviours and/or predict next actions/behaviours. For instance, SCAN [63], [64], [65] and [69] use various sensors to classify activities, while systems like MavHome [16] and [74] extend this scope with prediction. When privacy is a key, some systems make use of non-intrusive sensors [69, 22] or they change the way data are handled and presented accordingly [39, 64, 65]. It should be noted that data-driven approaches presented in the described works are appropriate when semantics is not a key and that there is enough annotated data and good processing power available. Furthermore, when IoT devices are subject to changes, the need for training data enforces to re-train data to adapt to changes in devices and can be a drawback of these approaches. Concerning data-driven algorithms, regardless of the theoretical model used (ad-hoc models or mature models including MM, NN, BN), they are usually not reusable as they do not offer abstract reasoning mechanisms based on semantics. That's why hybrid approaches were developed to benefit from the strength of both knowledge-based and data-driven approaches and to mitigate their shortcomings.

Hybrid approaches

A third category, hybrid approaches, has emerged to combine both strengths of knowledge-based and data-driven models. The last decade is also prominent in AAL services implemented this way.

Hybrid-approaches also rely on basic services such as activity recognition.

[68] presents a system that recognizes ADLs using a Kinect RGB-D Camera. First, Dynamic Time Warping algorithm learns and recognizes sub-activities (e.g. reaching, opening) that are used in a second time by a FuzzyDL reasoner to recognize high-level activities (e.g. making cereal, taking medicine). Activities are represented in a fuzzy ontology that includes represented in a fuzzy ontology to include the semantic interpretation of actions performed by users and handles vagueness and uncertainty.

[49] propose a hybrid-approach based on computational narratives to interpret everyday activities. Various video and depth sources feed the author's Qualitative Spatial Representation and Reasoning (QSR) framework handling space, action and change representation, prediction or explanation. Activities are interpreted following Bayesian / Markov logic over the observation sequences.

Complete hybrid AAL systems are then built atop those basic services especially for medical purpose or user prompting.

In [34], pervasive healthcare monitoring is intended to offer a real-time interactive medical consultation, to predict risky situations and prompt the inhabitant in case of emergency. User's medical history, physiological and ambient data collected from various wearable and environmental sensors are represented in XML document. These data constitute the base for some Case-Based Reasoning (CBR). A case-based reasoning approach is used where retrieval and adaptation are handled by hierarchical fuzzy rules. A k-NN function is then applied to determine the best solution.

[36] propose a context-aware decision making under uncertainty for voice-based control of a smart home for people with reduced mobility, in emergency or in loss of autonomy. OWL2 ontologies are used to represent sensor and actuator raw data (e.g. microphones, infrared presence detectors, lights) at a low level, and at a reasoning level, concepts like activity, location and situations. The reasoning is

performed in many ways: ontologies are enriched with SWRL rules for situation recognition (e.g. "main door open"), location is inferred using temporal dynamic networks for multisource fusion and spreading activation, activity recognition and decision making (e.g. "turn on the ceiling light") are based on ML.

iMessenger [27] is an activity monitoring and reminder delivery framework built on top of ontological modelling and context extraction. It utilizes an OWL ontology built in Protégé-OWL to describe activities as a series of events at specific locations over a period. Accelerometer data is translated into postures using SVM, and indoor location is determined using an RFID system. SWRL rules with temporal reasoning are used to provide feedback based on the consistency or inconsistency between the user expected and observed behaviours.

[30] presents a smart home system that can recognize twenty common ADL. The system predicts, reasons, and interacts with the elderly through reminders and messages via a mobile phone and may also acts on the environment. Data from environmental sensors, RFID readers and user profile are represented in a taxonomy. To take in account vagueness and uncertainty of data collecting from diverse sources, a rough set theory helps building activity models as rule-based classification problems. Assistive actions are derived with CBR, followed by a rule-based reasoning that fine-tune the decision for a case.

[23] designed an architecture for AAL applied to the night-time wandering scenario. An OWL ontology is used to represent the user scenarios of daily living inside the physical environment. Various reasoning approaches such as ontological reasoning, fuzzy logic, BNs or rules are used to determine activities and assist the resident.

Another notable mention is CoCaMAAL, with which Forkan et al. [4, 51] aim to detect long-term behavioural change and predict abnormality in an AAL. CoCaMAAL relies on user traces about presence, vital signs, activities and life patterns to detect changes in the daily living habits or health conditions. An ontology stores information about persons, places, environment and devices, which is then translated into XML to train an HMM. Pushing the current context into this HMM allows the system to detect if an abnormal behaviour or long-term change is happening.

BDCaM [55] is an extension of CoCaMAAL dedicated for people with limited mobility, regarding situations of loss of autonomy and emergency. They propose a context-aware decision making under uncertainty and based on big data. OWL2 ontologies are used to represent sensor and actuator raw data at a low level. Reasoning, based on concepts like activity, location and situations. The reasoning is performed in various ways. Ontologies are enriched with SWRL rules when a specific situation is recognized (e.g. "main door open"). Location is inferred using temporal dynamic networks for multisource fusion and spreading activation. Activity recognition and decision making are based on ML.

Finally, optimal service delivery is discussed in [37] with a context-aware application that provides services according to a predefined preference of a user. The system collects raw sensor data into a database and uses an ontology to draw high-level context. Based on context data here called service-triggering information, a k-

NN classifier combined with an ontology-based context modelling infers the predefined service that will maximize user's satisfaction.

An overview of the presented hybrid works points out that the integration of knowledge-based and data-driven techniques could help building systems that are capable of semantic interpretation and logic reasoning while taking advantage on historicized and sometimes imprecise data collected over time to recognize habits and predict the future. In this way, systems like iMessenger [27], [68], [30] and [23] make use of data-driven models to derive low-level context information in real time (opening, moving, reaching, etc.) that are then used by ontology-based rule reasoning mechanisms to derive upper-level context knowledge (activities, posture, location, etc.) and provide feedback adapted to situations. On the contrary, systems like [55], [36] and [37] do the inverse by rather using ontologies for situation recognition and data-driven models for decision making. No matter the way you go, hybrid systems can become cumbersome if not well managed and should be implemented carefully to not fall into unnecessary big, complicated and costly systems that function poorly.

Comparison between approaches

Table 1 to Table 6 resume the links between services and reasoning approaches. The tables list all the reviewed articles, grouped according to the service they deliver. Each table is dispatched between data-driven, knowledge-driven and hybrid approach. The reference number identifies the article and the type of gathered data, the context modelling and context reasoning are mentioned when available.

The first three tables present the basic services. Most of the basic services concern activity recognition (Table 1). No knowledge driven approach is used for fall detection (Table 3). At the reverse, recommendation systems, which are dedicated to medical caregivers, are only based on knowledge driven approaches (Table 6).

Table 1: Basic Service - Activity recognition

Data	**Context modelling**	**Context reasoning**	**Ref.**
	Data – driven approach		
Camera image (low-level included) and depth image	GMM, MCBS for object interaction/activity recognition		[39]
	HMM based on mobility patterns and sleep duration	k-NN	[22]
	SVM trained with SMO	X-means	[65]
Wearable sensor data	Classifier (Logistic Regression, Random Forest, ERT, SVM, k-NN, BN)		[58]

Any sensor data, Time, Presence	NN alike		[62]
Radio devices	CNN over RTI		[45]
Any sensor data	User interaction with objects as a series of beats	Custom rules	[63]
	Frequent pattern mining with presented algorithm and mapping function		[69]
Knowledge – driven approach: ontology			
Any sensor data	Sensors, physical environment, activities	Pellet reasoner, time-window algorithm	[61]
		Rules	[44]
	User personality, devices, OWL time		[28]
	Physical environment, ADLs	ML, RDF Batch reasoning, Spatiotemporal reasoning (Geo-SPARQL)	[7]
Pressure, contact, ultrasonic sensors data	(CoSSN): activities, observation, features of interest, cognitive stimulus	SPARQL rules	[42]
Environmental and body sensors data	Sensors, events, situations, time intervals, physical environment	Logic-rules and non-monotonic reasoning (Answer Set Programming)	[3]
	Sensors, events, time, dementia related (DUL)	OWL2 reasoning	[40]
Hybrid approach			
Environmental and body sensors data	XML: medical data, wearable and ambient sensors	CBR: Fuzzy rules for retrieval and adaptation, k-NN selection	[34]
Accelerometer data, RFID tags	Ontology: physical environment places linked to RFID, activities as events linked to posture and places	Kalman filters and SVM classification of activities. Activity consistency validation through SWRL and SQWRL rules	[27]
Camera image (low-level included) and depth image	Fuzzy ontology: Activities as sequential execution of sub-activities	k-NN for sub-activity recognition on the posture. Fuzzy rules for high-level activity recognition	[68]
	CLP (QSR), Bayesian/Markov model		[49]

Any sensor data	Ontology: physical environment, devices, appliances, activities	Ontological reasoning, fuzzy logic, BNs, rules	[23]

Table 2: Basic Service - Posture recognition

Data	**Context modelling**	**Context reasoning**	**Ref.**
Data – driven approach			
Any sensor data	CNN from 2D images, transferred to RGB-D images; and SVM over skeleton model		[64]
Knowledge – driven approach: ontology			
Environment and body sensor data	Sensors, objects, events (interactions), actions performed	Activity recognition and body posture through OWL reasoning with HermiT	[43]
Hybrid approach			
Accelerometer data, RFID tags	Ontology: physical environment (RFID), activities (events with posture and place)	Kalman filters and SVM classification of activities. Activity consistency validation through SWRL and SQWRL rules	[27]

Table 3: Basic Service - Fall detection

Data	**Context modelling**	**Context reasoning**	**Ref.**
Data – driven approach			
Camera and depth	GMM, Multi-cue background subtraction for object interaction/activity recognition		[39]
Hybrid approach			
Accelerometer data, RFID tags	Ontology: physical environment (RFID), activities (events with posture and place)	Kalman filters and SVM classification of activity. Consistency validation through SWRL and SQWRL rules	[27]

Predictive services use basic services to predict next activities, behaviours or position. They are part of emergency services in order to prevent hazardous situations. Table 4 lists the papers that focus on predictive services even if other ones mention to make prediction.

Table 4: Predictive services

Service	Data	Context modelling	Context reasoning	Ref.
Data-Driven approach				
Next activity	Sequence of actions	Markov chain of events	Current state highest probability	[16, 50]
Future behaviours	motion and door entry point	Time series, start time/duration parameters	Recurrent NN	[74]
Knowledge-Driven approach				
Navigation	User well-known places, position (GPS)	Fuzzy sets	Fuzzy logic	[48]
Emergency prevention	Environmental and body sensor	Ontology: sensors, events, situations, time intervals, physical environment	Logic-rules and non-monotonic reasoning (Answer Set Programming)	[3]
	Environmental and body sensor, physiological and medical status, Bluetooth bracelet presence	Ontology: ACCIO-based (physical space, sensors, medical observations, nurses, patients, etc.) plus medical symptoms, diagnoses, faults	Semantic annotation at the reception, C-SPARQL/Custom rules	[18]
Hybrid approach				
Future behaviours	User traces about presence, physiological data, activities, life patterns	Ontology: persons (profile, habits), physical space (places), devices	HMM classifier trained with XML representation of the ontology	[4, 51]
			Above plus supervised learning to improve user and general rules	[55]
Emergency prevention	Environmental and body sensor data	XML: medical data, wearable and ambient sensors	CBR: Fuzzy-rules for case retrieval and adaptation, k-NN for selection	[34]

Most AAL systems for inhabitants combine various services offering ambient assistance as well as alert in case of emergency. Home automation services are also included in ambient assistance when the AAL service modifies the physical environment to offer a comfortable ambiance personalized according to time of the day and activities. Table 5 resumes all the services for inhabitants.

Table 5: Services for inhabitants

Data	Context modelling	Context reasoning	Ref.
	Data – driven approach		
Binary sensor data	Markov chain with CLS and presented assumption		[38]
Any sensor data	Multilayer perceptron neural network, classification algorithms		[32]
User traces	Markov chain of user traces and interactions with the system		[16, 50]
	Knowledge – driven approach: ontology		
Any sensor data, user profile, service requests	Physical environment, sensors, user profile	Fuzzy rules	[71]
User control logs	User, devices and their effects, basic services, locations, AAL system	Adequate device/service activation through SWRL rules	[72]
Low-level sensor datastream	Patient physiological metrics, physical environment actions, sensor events	Inferring Healthcare-related high-level data through inference rules	[5]
Sensors data, interaction context	Meta-concepts, events, queries and facts, scenarios or knowledge. SQL Database for agent memory	Situation recognition and assistance through ontological reasoning and virtual reality simulation	[33]
Sensors data as events	User personality, devices, time (OWL Time)	Rules	[28]
Wireless sensor, actuator and smart meter data	Smart building, environment parameters and devices	Rules, Defeasible logic	[60]
Any sensor data	Seven ontologies: 1) sensors, actuators, medical devices, appliances 2) actions, activities 3) physical space 4) actors 5) medical information 6) services/applications 7) time	SPARQL rules	[17]
Speech	Ontology: sensor data, medical data, user preferences, nonverbal data (gestures, face), conversations themes and topics	SPIN/SHACL rules, non-monotonic rules for context disambiguation	[29]
Environmental kitchen sensor data		Ontological reasoning over Hierarchical Task	[24, 35]

		Network-inspired scenarios	
Hybrid approach			
Speech, infrared presence detectors, lights	Ontology: sensors (microphone, infrared presence detectors, lights), activities, physical environment places, situations	SWRL rules for situation recognition, Temporal Dynamic Networks for location inference, ML activity recognition and decision making	[36, 55]
Environmental sensors data, RFID readers, body sensors, camera image	Contextual labels: User profile (name, sex, age, preferences), Tasks, Social situation, Temporality, Environment	SPARQL rules, CBR	[30]
Any sensor data, user preferences	Ontology: person and relations, time frames, locations, activities	k-NN to select the service that will maximize user's satisfaction	[37]
Environment and body sensor data	XML: medical data, wearable and ambient sensors	CBR: Fuzzy rules for case retrieval and adaptation, k-NN for selection	[34]
Any sensor data	Ontology: physical environment, devices, appliances, activities	Ontological reasoning, fuzzy logic, Bayesian networks, rules	[23]
Accelerometer data (smartphone), RFID tags	Ontology: physical environment places linked to RFID, activities as events linked to posture and places	Kalman filters and SVM classification of activities. Activity consistency validation through SWRL and SQWRL rules	[27]

Among the services for caregivers, the articles reviewed refer on services to formal caregivers (Table 6). They concern most often medical services.

Table 6: Services for caregivers

Data	Context modelling	Context reasoning	Ref.
Knowledge – driven approach: ontology			
Patient tests (discrete physiological data)	Anti-diabetic drugs (medicine, composition, contraindication, HbA1c%), patient tests	SWRL rules, JESS reasoning	[26]
	Chronical illness signs, symptoms, interventions, assessments, syndromes. Tailored to the patient	Inference / Counting properties	[25]

Any sensor data	Sensors, events, time, dementia related (DUL)	Activity recognition with OWL2 reasoning, Non-pharmaceutical interventions through SPARQL rules	[40]

Discussion

The last decade works on context aware AAL have been extensively presented to derive a trend among context modelling and reasoning. Some findings from previous reviews are still accurate [12, 75]. Key-Value [4] and Markup language like XML [34] are still used to store context data for data-driven reasoning. However, other approaches like Key-Value, Markup and Object-Oriented modelling, which have been widely used ten years ago to capture domain knowledge tend to disappear in knowledge-based systems to be replaced by ontologies.

In the following, we explore what influences the choice of context modelling and reasoning. Starting with the context data, specifically its nature and the sensors used to collect data, we then show how some services induce the type of modelling.

Considering the recent literature, when it comes to choose convenient context modelling and reasoning approach for service implementation, some other issues have been raised up beyond the service itself: nature of data and types of sensors.

Nature of data

Nature of data is important for decision making. In fact, inaccurate data lead to poor decisions and then to irrelevant services. Sometimes it happens that sensors stop working or worse give non-sense data. These device failures generate uncertain or incomplete data. In addition, inhabitants themselves can be source of uncertainty. For instance, they may leave home for a long time to go on holidays or to hospital. If they forgot to turn off the AAL system, data are still collected leading to errors in decision. At the reverse, inhabitants who usually live alone may invite guests who introduce confusion in the data collected. To deal with this uncertainty and vagueness in data, some context models include fuzzy sets [48], and fuzzy ontologies [76] while reasoning is performed with fuzzy logics [48], fuzzy rules [34, 46], BNs [23, 49] and Markov logics [36, 49, 50].

Visual sensors

Either low-resolution visual sensors [22] or high resolution RGB-D cameras [64, 68] require computer vision algorithms for data-driven analysis and exploitation. In this way, k-NN [68][22], GMM [39], MM [22, 49], SVM [27, 64, 65], NN [62], Dynamic Time Warping [68] and CBR [30, 34] are used to classify user activities, body postures and falls in AAL systems.

Biosensors

The wide adoption of wearable biosensors among people leads to increase the amount of collected data and the number of advanced pervasive healthcare systems. It was expected that this increase of digital data would promote data-driven approaches for health monitoring. However, ontologies are the most used context model, combined with rule reasoning (either classic, fuzzy or non-monotonic) for prompt and alert propagation, emergency and recommendations in health monitoring systems [3, 5, 18, 25, 30, 77]. These systems can turn hybrid when data-driven reasoning is added to achieve more accurate results or to extend the services with anomaly detection and the prediction of future behaviours. It is the case with k-NN [34], MM [4, 51] or supervised learning [55] is added to achieve more accurate results or to extend the services with anomaly detection and the prediction of future behaviours.

Activity, body posture and fall recognition services

As previously stated, data-driven classification models are the most used when the environment is equipped with visual sensors. However, visual sensors are not always appropriate due to the high cost of high-resolution cameras, the need for a performing machine processing and privacy issues. To avoid such inconvenience several AAL systems make use of other types of sensors, more affordable and privacy compliant. Wearable sensors and non-visual ambient sensors include among others, accelerometers, Passive InfraRed, contact, mobile phones. Therefore, data-driven models are used only occasionally, such as SVM [58] and CNN [45]. The reasoning approach is more likely knowledge based. Ontologies with rule reasoning are largely prominent [3, 7, 28, 40, 42, 44, 61]. They are sometimes coupled with SVM [27] and BN [23].

Predictive services

Predictive services are most often based on historical context data. The significant amount of available data collected from multiple sensors collected over time suggests the prevalence of data-driven models. In fact, the review shows that MM has been used for predicting the next activity [78, 79] and inhabitants' future behaviours [51, 55]. NN also appears to be a useful model to improve reasoning on temporal for sequential or parallel activities. NN is also used to predict future anomalous behaviours [74]. The prediction of future health state and prevention of health emergency relies most often on physiological data that are gathered by biosensors.

These predictions are widely handled by ontologies and rule reasoning [3, 18]. They can be extended with data-driven reasoning to efficiently take advantage on historical data like k-NN to refine CBR [34].

Temporal reasoning

Managing time-stamped data and representing temporal relationships are essential in AAL systems, whether to detect or predict activity, body posture or fall, to offer ambient assistance, home automation and navigation services, or in case of emergency. The most obvious finding of this review is the wide use of use of ontologies to implement various types of AAL services, Decision making is then provided with OWL or SPARQL rules. This is a bit surprising while weaknesses of ontologies have been widely reported, especially regarding the difficulty to deal with temporal data [80, 81]. On the opposite, the efficiency of MM and NN has been established [74, 82]. This preponderant use of ontologies can be explained by many efforts that have been done to overcome this weakness. For instance, the development of Time Ontology2 (OWL-Time) as a W3C recommendation helps describing temporal properties of resources in ontologies. OWL-Time is used in some of the reviewed works [17, 28, 40]. In the same vein, ontologies are also coupled with data-driven models to enhance time management [7, 37, 46, 68]

Services for inhabitants

Services for inhabitants provide direct assistance, either for comfort, for daily task execution or in case of emergency. The review shows that a pure data-driven approach like in [32] is rare. Most of the time, a knowledge-based approach, such as an ontology, represents information and rules are triggered for decision-making, such as SWRL and SPARQL rules. SPIN, fuzzy rules and defeasible rules often appear to derive adapted and personalized services to the user or to give alert in case of emergency. Hybrid approaches are also common for the provision of services to inhabitants. In fact, ontological reasoning is enhanced by associating data-driven approaches like BN [23], Markov logics [36] and k-NN [37] to ontologies.

This intensive use of ontologies to describe services for inhabitants can be explained by the fact that these services rely on the knowledge the system has on environment and the inhabitant. It means to be able to describe the home and the installed devices, including those for user-home communication. It also implies to be able to specify the capacities, the deficits and the preferences of inhabitants. In

2 https://www.w3.org/TR/owl-time/

addition, the structure and the shareable nature of ontologies favour their integration with other models like data-driven ones.

Conclusion

Many context and reasoning models have been proposed in the last decade to capture context data and extract relevant knowledge for decision making in ever changing environments. AAL systems, which make use intensively of IoT devices and algorithms, aim to offer comfort, safety, assistance, and monitoring. In this review of literature, we have adopted two guidelines, first to review more specifically the context-aware AAL systems dedicated for people with specific needs, second to present the review from a service-oriented perspective. Our hypothesis was that the nature of services and the types of collected data impact the choice of modelling and reasoning on context.

To this end, several AAL systems of different types developed in the last decade have been investigated. We classify them in three groups: basic services, which are usually prerequisite for more elaborated ones, services usually provided to improving the lifestyle of inhabitants and the services that enable caregivers to monitor inhabitant's actions in the AAL environment. We then clarify context awareness terminologies and the data mainly gathered in AAL. An extensive and comprehensive review of selected works has been carried out to derive technical development trends in terms of context modelling and reasoning for AAL service provision. To resume the reasoning approaches it is worth pointing out they are separated into two broad schools of thought: knowledge-driven approaches where ontologies enriched by logical rules are preponderant, and data-driven approaches where supervised and unsupervised classification techniques among others are prevailing. A third approach aims to benefit from the strengths of the two previous ones by combining them into a hybrid approach.

Some trends in choosing context modelling have emerged from this review. First, the types of sensors influence data modelling and reasoning. Numerous digital data collected by cameras implies the use of data-driven models for activity, body posture and fall classification. When other ambient sensors are used, ontologies are favoured for those services and sometimes are combined with data-driven models. Biosensors used in health monitoring produce data more often handled in ontologies or hybrid systems. This approach is completed by various data-driven models to deliver more accurately prompts, alerts and recommendations. Whatever the delivered service, uncertainty and vagueness coming from data force to complete the initial approaches. Fuzzy sets, fuzzy ontologies and fuzzy rules are added in knowledge-based approach; BN and MM are widely used in data-driven approaches.

No trend is emerging from services to caregivers. However, regarding the implementation of services to inhabitants, research efforts are converging toward knowledge representation in ontologies and rule reasoning. Data-driven reasoning completes occasionally this approach. When it comes to predict the future, data-driven models like MM and NN take advantage on historical data collected over time to provide relevant insights on the events more likely to occur.

In the future, it is expected that the IoT market diversify its products. AAL systems tend also to become more complex, offering more than one service. It appears then that in the future AAL system will mix different approaches, by using the most convenient one to implement a specific service or group of services. The challenge will be in an optimal combination, to take advantage of them instead of getting lost in a myriad of models. We do not pretend to have covered all the services available in AAL systems, even less to predict the next years. We neither intend to make a critical review of the works presented. However, this work has tried to give an insight of the most suitable modelling and reasoning technique to select for a given AAL service.

Glossary

AAL	Ambient Assisted Living
ADL	Activity of Daily Living
BN	Bayesian Network
CBR	Case-Based Reasoning
CNN	Convolutional Neural Network
ERT	Extremely Randomized Tree
GMM	Gaussian Mixture Model
HMM	Hidden Markov Model
ICF	International Classification of Functioning
IoT	Internet of Things
k-NN	k-Nearest Neighbours
MCBS	Multi-Cue Background Subtraction
MCI	Mild Cognitive Impairment
ML	Machine Learning
MM	Markov Model
NN	Neural Network
QSR	Qualitative Spatial Representation and Reasoning
RFID	Radio Frequency IDentification
RGB-D	Red Green Blue-Depth
RNN	Recurrent Neural Network
RTI	Radio Tomographic Imaging
SAT	Boolean SATisfiability problem
SMO	Sequential Minimal Optimization
SVM	Support Vector Machine

References

1. Baldauf M, Dustdar S, Rosenberg F (2007) A survey on context-aware systems. Int J Ad Hoc Ubiquitous Comput 2:263–277
2. Rashidi P, Mihailidis A (2013) A survey on ambient-assisted living tools for older adults. IEEE J Biomed Heal Informatics 17:579–590. https://doi.org/10.1109/JBHI.2012.2234129
3. Alirezaie M, Renoux J, Köckemann U, et al (2017) An Ontology-based Context-aware System for Smart Homes: E-care@home. Sensors 17:1586. https://doi.org/10.3390/s17071586
4. Forkan A, Khalil I, Tari Z (2014) CoCaMAAL: A cloud-oriented context-aware middleware in ambient assisted living. Futur Gener Comput Syst 35:114–127. https://doi.org/10.1016/j.future.2013.07.009
5. Aritoni O, Negru V (2010) Sensors data-stream processing middleware based on multi-agent model. Scalable Comput 11:19–32. https://doi.org/10.12694/scpe.v11i1.636
6. Klimek R (2018) Exploration of Human Activities Using Message Streaming Brokers and Automated Logical Reasoning for Ambient-Assisted Services. IEEE Access 6:27127–27155. https://doi.org/10.1109/ACCESS.2018.2834532
7. Preuveneers D, Berbers Y, Joosen W (2016) SAMURAI: A batch and streaming context architecture for large-scale intelligent applications and environments. J Ambient Intell Smart Environ 8:63–78. https://doi.org/10.3233/AIS-150357
8. Magableh B, Albeiruti N (2012) Detecting the onset of dementia using context-oriented architecture. In: Proceedings - 6th International Conference on Next Generation Mobile Applications, Services, and Technologies, NGMAST 2012. pp 24–30
9. Dey AK, Abowd GD, Salber D (2000) A Context-Based Infrastructure for Smart Environments. In: Managing Interactions in Smart Environments. pp 114–128
10. Bettini C, Brdiczka O, Henricksen K, et al (2010) A survey of context modelling and reasoning techniques. Pervasive Mob Comput 6:161–180. https://doi.org/10.1016/j.pmcj.2009.06.002
11. El murabet A, Abtoy A, Touhafi A, Tahiri A (2018) Ambient Assisted living system's models and architectures: A survey of the state of the art. J. King Saud Univ. - Comput. Inf. Sci. 32:1–10
12. Li X, Eckert M, Martinez JF, Rubio G (2015) Context aware middleware architectures: Survey and challenges. Sensors (Switzerland) 15:20570–20607. https://doi.org/10.3390/s150820570
13. Perera C, Zaslavsky A, Christen P, Georgakopoulos D (2014) Context aware computing for the internet of things: A survey. IEEE Commun Surv Tutorials 16:414–454. https://doi.org/10.1109/SURV.2013.042313.00197
14. Alam MR, Reaz MBI, Ali MAM (2012) A review of smart homes - Past, present, and future. IEEE Trans Syst Man Cybern Part C Appl Rev 42:1190–1203. https://doi.org/10.1109/TSMCC.2012.2189204
15. Camarinha-Matos LM, Ferrada F, Oliveira AI, et al (2014) Care services provision in ambient assisted living. IRBM 35:286–298. https://doi.org/10.1016/j.irbm.2014.08.001
16. Cook DJ, Youngblood M, Heierman EO, et al (2003) MavHome: An agent-based smart home. In: Proceedings of the 1st IEEE International Conference on Pervasive Computing and Communications, PerCom 2003. pp 521–524
17. Chen L, Nugent C (2010) Situation aware cognitive assistance in smart homes. J Mob Multimed 6:263–280
18. De Brouwer M, Ongenae F, Bonte P, De Turck F (2018) Towards a cascading reasoning framework to support responsive ambient-intelligent healthcare interventions. Sensors (Switzerland) 18:. https://doi.org/10.3390/s18103514
19. Wojciechowski M (2010) End User Context Modeling in Ambient Assisted Living. Int J Adv Pervasive Ubiquitous Comput 1:61–80. https://doi.org/10.4018/japuc.2009090804

20. Mocholí JB, Sala P, Naranjo JC (2010) Ontology for Modeling Interaction in Ambient Assisted Living Environments. In: XII Mediterranean Conference on Medical and Biological Engineering and Computing 2010
21. Ayari N, Chibani A, Amirat Y, Matson E (2016) A semantic approach for enhancing assistive services in ubiquitous robotics. Rob Auton Syst 75:17–27. https://doi.org/10.1016/j.robot.2014.10.022
22. Eldib M, Deboeverie F, Philips W, Aghajan H (2016) Behavior analysis for elderly care using a network of low-resolution visual sensors. J Electron Imaging 25:041003. https://doi.org/10.1117/1.jei.25.4.041003
23. Kenfack Ngankam H, Pigot H, Lorrain D, et al (2020) Context awareness architecture for ambient-assisted living applications: Case study of nighttime wandering. J Rehabil Assist Technol Eng 7:205566831988786. https://doi.org/10.1177/2055668319887864
24. Pinard S, Bottari C, Laliberté C, et al (2019) Design and usability evaluation of COOK, an assistive technology for meal preparation for persons with severe TBI. Disabil Rehabil Assist Technol 1–15. https://doi.org/10.1080/17483107.2019.1696898
25. Riaño D, Real F, López-Vallverdú JA, et al (2012) An ontology-based personalization of health-care knowledge to support clinical decisions for chronically ill patients. J Biomed Inform 45:429–446. https://doi.org/10.1016/j.jbi.2011.12.008
26. Chen RC, Huang YH, Bau CT, Chen SM (2012) A recommendation system based on domain ontology and SWRL for anti-diabetic drugs selection. Expert Syst Appl 39:3995–4006. https://doi.org/10.1016/j.eswa.2011.09.061
27. Zhang S, McCullagh P, Nugent C, et al (2013) An ontological framework for activity monitoring and reminder reasoning in an assisted environment. J Ambient Intell Humaniz Comput 4:157–168. https://doi.org/10.1007/s12652-011-0063-1
28. Jacquet C, Mateos M, Bretault P, et al (2012) An Ambient Assisted Living Framework Supporting Personalization Based on Ontologies. In: in AMBIENT 2012, the Second International Conference on Ambient Computing, Applications, Services and Technologies. IARIA
29. Meditskos G, Kontopoulos E, Vrochidis S, Kompatsiaris I (2019) Converness: Ontology-driven conversational awareness and context understanding in multimodal dialogue systems. In: Expert Systems. Blackwell Publishing Ltd
30. Zhou F, Jiao J, Chen S, Zhang D (2011) A case-driven ambient intelligence system for elderly in-home assistance applications. IEEE Trans Syst Man Cybern Part C Appl Rev 41:179–189. https://doi.org/10.1109/TSMCC.2010.2052456
31. Skillen K-L, Chen L, Nugent CD, et al (2014) Ontological user modelling and semantic rule-based reasoning for personalisation of Help-On-Demand services in pervasive environments. Futur Gener Comput Syst 34:97–109. https://doi.org/10.1016/J.FUTURE.2013.10.027
32. Costa N, Domingues P, Fdez-Riverola F, Pereira A (2014) A mobile virtual butler to bridge the gap between users and ambient assisted living: A smart home case study. Sensors (Switzerland) 14:14302–14329. https://doi.org/10.3390/s140814302
33. Adjali O, Hina MD, Dourlens S, Ramdane-Cherif A (2015) Multimodal fusion, fission and virtual reality simulation for an ambient robotic intelligence. In: Procedia Computer Science. Elsevier B.V., pp 218–225
34. Yuan B, Herbert J (2014) Context-aware hybrid reasoning framework for pervasive healthcare. Pers Ubiquitous Comput 18:865–881. https://doi.org/10.1007/s00779-013-0696-5
35. Olivares M, Giroux S, De Loor P, et al (2016) An ontology model for a context-aware preventive assistance system: reducing exposition of individuals with Traumatic Brain Injury to dangerous situations during meal preparation. In: 2nd IET International Conference on Technologies for Active and Assisted Living (TechAAL 2016). Institution of Engineering and Technology, pp 3 (8 .)-3 (8 .)
36. Chahuara P, Portet F, Vacher M (2017) Context-aware decision making under uncertainty for voice-based control of smart home. Expert Syst Appl 75:63–79. https://doi.org/10.1016/j.eswa.2017.01.014

37. Humayun Kabir M, Robiul Hoque M, Yang SH (2015) Development of a smart home context-aware application: A machine learning based approach. Int J Smart Home 9:217–226. https://doi.org/10.14257/ijsh.2015.9.1.23
38. Ghasemi V, Pouyan AA (2017) Modeling Users' Data Traces in Multi-Resident Ambient Assisted Living Environments. Int J Comput Intell Syst 10:1289. https://doi.org/10.2991/ijcis.10.1.88
39. Padilla-López JR, Chaaraoui AA, Gu F, Flórez-Revuelta F (2015) Visual privacy by context: Proposal and evaluation of a level-based visualisation scheme. Sensors (Switzerland) 15:12959–12982. https://doi.org/10.3390/s150612959
40. Andreadis S, Stavropoulos TG, Meditskos G, Kompatsiaris I (2016) Dem@Home: Ambient Intelligence for Clinical Support of People Living with Dementia. In: CEUR Workshop Proceedings
41. Bergeron F, Giroux S, Bouchard K, Gaboury S (2017) RFID based activities of daily living recognition. In: 2017 IEEE SmartWorld Ubiquitous Intelligence and Computing, Advanced and Trusted Computed, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People and Smart City Innovation, SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI 2017 -. IEEE, pp 1–5
42. Zgheib R, Nicola A De, Villani ML, et al (2017) A flexible architecture for cognitive sensing of activities in ambient assisted living. In: Proceedings - 2017 IEEE 26th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises, WETICE 2017. Institute of Electrical and Electronics Engineers Inc., pp 284–289
43. Noor MHM, Salcic Z, Wang KIK (2018) Ontology-based sensor fusion activity recognition. J Ambient Intell Humaniz Comput 1–15. https://doi.org/10.1007/s12652-017-0668-0
44. Bennasar M, Price BA, Stuart A, et al (2019) Knowledge-based architecture for recognising activities of older people. In: Procedia Computer Science. Elsevier B.V., pp 590–599
45. Tan Z, Xu L, Zhong W, et al (2018) Online activity recognition and daily habit modeling for solitary elderly through indoor position-based stigmergy. Eng Appl Artif Intell 76:214–225. https://doi.org/10.1016/j.engappai.2018.08.009
46. Forkan ARM, Khalil I, Tari Z, et al (2015) A context-aware approach for long-term behavioural change detection and abnormality prediction in ambient assisted living. Pattern Recognit 48:628–641. https://doi.org/10.1016/j.patcog.2014.07.007
47. Bergeron F, Bouchard K, Gaboury S, Giroux S (2018) Tracking objects within a smart home. Expert Syst Appl 113:428–442. https://doi.org/10.1016/j.eswa.2018.07.009
48. Hervás R, Bravo J, Fontecha J (2014) An assistive navigation system based on augmented reality and context awareness for people with mild cognitive impairments. IEEE J Biomed Heal Informatics 18:368–374. https://doi.org/10.1109/JBHI.2013.2266480
49. Bhatt M, Suchan J, Schultz C (2013) Cognitive interpretation of everyday activities - Toward perceptual narrative based visuo-spatial scene interpretation. In: OpenAccess Series in Informatics. pp 24–29
50. Das SK, J. Cook D, Bhattacharya A, et al (2002) The role of prediction algorithms in the mavhome smart home architecture. IEEE Wirel Commun 77–84
51. Forkan ARM, Khalil I, Tari Z, et al (2015) A context-aware approach for long-term behavioural change detection and abnormality prediction in ambient assisted living. Pattern Recognit 48:628–641. https://doi.org/10.1016/j.patcog.2014.07.007
52. Psyché Valéryand Daniel B and BJ (2019) Adaptive Learning Spaces with Context-Awareness. In: Coy Andreand Hayashi Y and CM (ed) Intelligent Tutoring Systems. Springer International Publishing, Cham, pp 7–13
53. Bazire Maryand Brézillon P (2005) Understanding Context Before Using It. In: Dey Anindand Kokinov B and LD and TR (ed) Modeling and Using Context. Springer Berlin Heidelberg, Berlin, Heidelberg, pp 29–40
54. Ryan N, Pascoe J (1998) Enhanced reality fieldwork: the context-aware archaeological assistant. Comput Appl Archaeol

55. Forkan ARM, Khalil I, Ibaida A, Tari Z (2015) BDCaM: Big Data for Context-Aware Monitoring—A Personalized Knowledge Discovery Framework for Assisted Healthcare. IEEE Trans Cloud Comput 5:628–641. https://doi.org/10.1109/tcc.2015.2440269
56. Zerawa S-A, Pollhammer K, Turek T (2011) Simplifying Routine task using contactless smartcards. In: IEEE AFRICON Conference
57. López-Cózar R, Callejas Z (2010) Multimodal Dialogue for Ambient Intelligence and Smart Environments. In: Handbook of Ambient Intelligence and Smart Environments. Springer US, pp 559–579
58. Zdravevski E, Lameski P, Trajkovik V, et al (2017) Improving Activity Recognition Accuracy in Ambient-Assisted Living Systems by Automated Feature Engineering. IEEE Access 5:5262–5280. https://doi.org/10.1109/ACCESS.2017.2684913
59. Stucki G (2005) International Classification of Functioning, Disability, and Health (ICF). Am J Phys Med Rehabil 84:733–740. https://doi.org/10.1097/01.phm.0000179521.70639.83
60. Stavropoulos TG, Kontopoulos E, Bassiliades N, et al (2015) Rule-based approaches for energy savings in an ambient intelligence environment. Pervasive Mob Comput 19:1–23. https://doi.org/10.1016/j.pmcj.2014.05.001
61. Okeyo G, Chen L, Wang H, Sterritt R (2014) Dynamic sensor data segmentation for real-time knowledge-driven activity recognition. Pervasive Mob Comput 10:155–172. https://doi.org/10.1016/j.pmcj.2012.11.004
62. Velik R (2014) A brain-inspired multimodal data mining approach for human activity recognition in elderly homes. J Ambient Intell Smart Environ 6:447–468. https://doi.org/10.3233/AIS-140266
63. Martínez-Pérez FE, González-Fraga JÁ, Cuevas-Tello JC, Rodríguez MD (2012) Activity inference for ambient intelligence through handling artifacts in a healthcare environment. Sensors 12:1072–1099. https://doi.org/10.3390/s120101072
64. El Amine Elforaici M, Chaaraoui I, Bouachir W, et al (2018) Posture recognition using an rgb-d camera: exploring 3d body modeling and deep learning approaches. In: 2018 IEEE Life Sciences Conference, LSC 2018. pp 69–72
65. Manzi A, Dario P, Cavallo F (2017) A human activity recognition system based on dynamic clustering of skeleton data. Sensors (Switzerland) 17:. https://doi.org/10.3390/s17051100
66. Allen JF (1983) Maintaining knowledge about temporal intervals. Commun ACM 26:832–843. https://doi.org/10.1145/182.358434
67. Hobbs JR, Pan F (2017) Time Ontology in OWL : Candidate Recommendation. In: W3C Consort. https://www.w3.org/TR/owl-time/
68. Díaz-Rodríguez N, Cadahía OL, Cuéllar MP, et al (2014) Handling real-world context awareness, uncertainty and vagueness in real-time human activity tracking and recognition with a fuzzy ontology-based hybrid method. Sensors (Switzerland) 14:18131–18171. https://doi.org/10.3390/s141018131
69. Chikhaoui B, Wang S, Pigot H (2011) A Frequent Pattern Mining Approach for ADLs Recognition in Smart Environments. In: Proceedings of the 25th international conference on Advanced Information Networking and Applications. pp 248–255
70. Abdulrazak B, Chikhaoui B, Gouin-Vallerand C, Fraikin B (2010) A Standard Ontology for Smart Spaces. IJWGS 6:
71. Gouin-Vallerand C, Abdulrazak B, Giroux S, Dey AK (2013) A context-aware service provision system for smart environments based on the user interaction modalities. J Ambient Intell Smart Environ 5:47–64. https://doi.org/10.3233/AIS-120190
72. Allègre W, Burger T, Antoine JY, et al (2013) A non-intrusive context-aware system for ambient assisted living in smart home. In: Health and Technology. pp 129–138
73. Tan Z, Xu L, Zhong W, et al (2018) Online activity recognition and daily habit modeling for solitary elderly through indoor position-based stigmergy. Eng Appl Artif Intell 76:214–225. https://doi.org/10.1016/J.ENGAPPAI.2018.08.009

74. Lotfi A, Langensiepen C, Mahmoud SM, Akhlaghinia MJ (2012) Smart homes for the elderly dementia sufferers: Identification and prediction of abnormal behaviour. J Ambient Intell Humaniz Comput 3:205–218. https://doi.org/10.1007/s12652-010-0043-x
75. Castillejo E, Almeida A, López-De-Ipiña D, Chen L (2014) Modeling users, context and devices for Ambient Assisted Living environments. Sensors (Switzerland) 14:5354–5391
76. Rodríguez ND, Cuéllar MP, Lilius J, Calvo-Flores MD (2014) A survey on ontologies for human behavior recognition. ACM Comput. Surv. 46
77. Chen L, Nugent CD, Wang H (2012) A knowledge-driven approach to activity recognition in smart homes. IEEE Trans Knowl Data Eng 24:961–974. https://doi.org/10.1109/TKDE.2011.51
78. Das SK, Cook DJ, Bhattacharya A, et al (2002) The role of prediction algorithms in the MavHome smart home architecture. IEEE Wirel Commun 9:77–84. https://doi.org/10.1109/MWC.2002.1160085
79. Cook DJ, Youngblood M, Heierman EO, et al (2003) MavHome: an agent-based smart home. In: Proceedings of the First IEEE International Conference on Pervasive Computing and Communications, 2003. (PerCom 2003). IEEE Comput. Soc, Fort Worth, TX, USA, pp 521–524
80. O'Connor MJ, Hernandez G, Das A (2011) A Rule-Based Method for Specifying and Querying Temporal Abstractions. In: Peleg M, Lavrač N, Combi C (eds) Artificial Intelligence in Medicine. Springer Berlin Heidelberg, Berlin, Heidelberg, pp 255–259
81. Weichert F, Mertens C, Walczak L, et al (2013) A novel approach for connecting temporal-ontologies with blood flow simulations. J Biomed Inform 46:470–479. https://doi.org/10.1016/j.jbi.2013.03.004
82. Lotte F, Bougrain L, Cichocki A, et al (2018) A review of classification algorithms for EEG-based brain-computer interfaces: A 10 year update. J. Neural Eng. 15