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REVIEW PAPER

Context awareness in healthcare: a systematic literature review

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Abstract
The incorporation of information and communication technologies has transformed the health field. With the constant miniaturization of embedded devices, the increase in human–computer interactions and their ubiquity has increased the possibilities of intervention in this field of study. One of the fundamental characteristics of ubiquitous computing applied to health is context awareness. The use of context awareness in healthcare faces many challenges, which has led to the search for several solutions in the integration of sensors from different origins, in data fusion and reasoning algorithms, among others. This paper aims to explore the recent literature related to the use of context awareness in health, defining the taxonomy and identifying challenges and open questions. The method for achieving these objectives is to use the systematic literature review approach, which is characterized by research questions that guide the definition of a taxonomy and the search for challenges in the area. As a result, we have reviewed around 4000 scientific studies published over the last ten years, selecting and researching the most meaningful, in-depth approaches in the field of context-aware health, resulting in a final corpus of 38 articles. We have developed an up-to-date taxonomy that classifies context awareness in the field of health, as well as identifying open questions and issues that can guide future work in the area. These results, unified in one paper, contribute to a significant degree of coverage of the use of context-aware data in health.

Keywords Survey · Health · Sensor · Wearable · Ubiquitous computing

1 Introduction

With the advancement and application of computational technology, ubiquitous computing is now used everywhere [15]. With the miniaturization of embedded devices as well as with the increasingly intelligent nature of software, human–computer interaction is continuously increasing. In addition to this interaction, the hardware and software must cooperate, thereby improving the human–machine interaction. One of the critical features of ubiquitous computing is context awareness [18, 60]. The idea of context awareness is to provide the appropriate services to users, such as smart homes, smart offices and health-related services [42, 43]. Also, currently the Internet of things (IoT) has been emerging as a new paradigm in information technology. The central idea is to build a dynamic network infrastructure, connecting a variety of physical and virtual "things" with the use of mobile devices and sensors. The practical use of these sensors on an Internet-connected platform raises many research possibilities, such as system architecture and application data processing [14, 23]. Collaborating with this, IoT technology has driven healthcare through a rapid proliferation of handheld devices and smartphones, from a conventional hub-based system to more personalized healthcare systems. However, enabling advanced IoT technology in custom systems is still a significant challenge in this field, suffering from problems such as the lack of accurate and economical medical sensors, non-standardized IoT system architectures, the heterogeneity of connected wearable devices, the multidimensionality of the data, and the high demand for interoperability [8, 48, 50].

Traditionally, the motivation to use information and communication technologies (ICT) in a health system is to provide medical services to patients, called e-health, such as electronic registration systems, telemedicine systems, and

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devices for diagnosis [50]. But with increasing longevity and the increase in the number of people with chronic diseases, there are problems with the economic viability of traditional health systems, thus generating the need to develop ubiquitous health systems to provide quality, patient-centered health services [10]. This includes, for example, the development of e-health systems applied to smart homes [43], systems for pervasive healthcare monitoring [1, 20, 53], and systems for senior wellness services in smart homes [31]. For the full functionality of these systems, we must consider the context, which is defined as any information that can be used to characterize the situation of a person, place or object deemed relevant to the interaction between a user and an application, where the relevance depends on the user's task. As a consequence, some desirable characteristics for context-aware systems in health are the presentation of information and services to a patient, the automatic execution of a function or the context tagging for later retrieval purposes [18]. Thus, in the health field, wearable sensors, such as accelerometers or ECG, are coupled to the patient to measure physiological and environmental data. These data are then analyzed to provide feedback for a variety of purposes, such as evaluating the effectiveness of a new treatment, better studying a disease, overcoming a patient's behavior, or adjusting medication. Context-sensitive healthcare applications face some common challenges, regardless of the ultimate goals [25, 52].

As examples of challenges related to the use of context awareness in health, we can mention the integration of heterogeneous sensor data, with different technologies, included in these networks and protocols [16, 22]. The energy efficiency of the sensors, as well as their responsiveness and robustness, are some of the challenges that arise [17, 38, 51]. Another challenge is context switching and continuous data delivery, without gaps [8, 10]. There are also issues related to the safety and privacy of the health information, which is important within the construction of the context where the patient is under care [5, 34, 63]. Finally, the increasing use of artificial intelligence/machine learning in healthcare has appeared as a significant trend [28], though it runs into the dilemma between vigilance and control on the one hand and support and personal benefit on the other [54]. Thus, considering the challenges cited and the fact that there are no documents that present these issues in a unified form, the objective of this article is to identify the technology in the use of context-aware health and to discuss the issues and challenges that surround the area, investigating the main contributions made in the last decade. A review was conducted of the literature on the use of context-aware data in the health field, describing the technologies involved and their uses. As a way of mapping the scenario, we used the method of a systematic review of the literature to choose a corpus of studies [11, 65]. As a result, we present an updated taxonomy and indicate the paths and challenges to be overcome for the application of context awareness in health.

This paper is organized as follows. In Section 2, we describe the study protocol used in the literature review. In Section 3, we describe the results of the research and evaluate the quality of the articles in the corpus. In Section 4, we answer and discuss the formulated research questions. In Section 5, we present the challenges and future directions for the use of context awareness in the health field. Finally, in Section 6, we present the conclusions and limitations of this paper.

2 Method

This section focuses on the description of the study protocol, which introduces the procedures adopted and guides subsequent decisions. Unlike a conventional and unstructured review process, a systematic review follows a rigorous sequence of methodological steps [11, 65]. Based on a well-defined and evaluated review protocol, this study presents a systematic literature review designed to provide a broader view of context awareness in healthcare research.

2.1 Study design

We chose the systematic literature review approach because a large number of articles can be combined and at the same time it can provide a summary, allowing gaps to be identified for future research. The systematic review of the literature is increasingly used in the health field, the central theme of this study, a factor that contributed to its adoption. The steps below define the scope of this systematic literature review (SLR) [55]:

1. Research questions: present the research questions used;
2. Search strategy: present the strategy and libraries exploited to collect the data;
3. Article selection: explain the criteria for selecting the studies;
4. Distribution of articles: present how the studies are distributed chronologically;
5. Quality assessment: assess the quality of the selected studies;
6. Data extraction: compare the selected studies with the research questions.

2.2 Research questions

Research questions are based on the motivation to conduct the SLR, that is, the answers to these questions should provide an evidence-based consolidation to define, apply and

Table 1 Research questions

Identifier	Issue
RQ1	How is the use of context awareness in the health field defined and classified in the existing research?
RQ2	What are the challenges related to the use of context-aware information in healthcare?
RQ3	What are the use case scenarios related to context awareness in healthcare?
RQ4	What are the context modeling techniques employed in healthcare?
RQ5	What are the reasoning and data fusion methods used in context-aware information in healthcare?

acquire knowledge about the use of context awareness in healthcare.

According to Table 1, question RQ1 concerns the definitions, classifications, and characterizations existing in the literature (if any). RQ2 relates to the challenges that arise in the use of context-aware information in the health field. Question RQ3 refers to scenarios in which context-aware data are applied, or its use has relevance to the health field. Question RQ4 seeks to identify and compare the evidence regarding context-aware health modeling methods. Finally, question RQ5 asks how contextual reasoning is presented, also including data fusion methods.

2.3 Search strategy

After defining the research questions, the next step was to select a set of studies related to the research questions. This process involves the definition of search keywords and the definition of the scope of the search [49]. The search keywords were defined after reading articles in the area of interest, and the separation of terms, synonyms, and acronyms that best defined the search object (taking into account its relation to previously defined research questions). Following what was defined by Kitchenham and Charters [32], these terms were combined using Boolean operators.

We define the scope of the work as the use of context-aware data in the health field. In this way, the final research chain, formed from the criteria described above, was defined as follows.

> **Search String**
>
> (Context aware OR Context awareness OR Situational Aware OR Situational Awareness) AND (Health OR HealthCare) AND (Environment data)

In the execution of the article search, the source studies were obtained from electronic databases, selected through searches using the keywords of the constructed string. The electronic databases included in the survey were: ACM Digital Library[1]; Google scholar[2]; IEEE Xplore Library[3]; IET Digital Library[4]; JMIR Publications[5]; PubMed[6]; ScienceDirect[7]; Springer Link[8]; Web of Science[9]; and Wiley Online Library[10].

These databases were chosen because they constitute a significant sample of the databases and provide full-text journals and conference proceedings of the most important health conferences involving e-health, wearables, and their relations.

2.4 Article selection

After collecting the set of related articles in the databases, we proceeded to remove studies that were not relevant, so as to maintain only the most representative ones. For this, after the initial search, the impurities were removed, which entailed the removal of duplicate articles (because some studies were available in more than one database), and articles not related to the search string, but which were returned due to characteristics of the different electronic databases.

After the first filter, the second and third filters consisted of analyzing the title and the abstract, respectively, and excluding those that did not mention health and context (according to the search string). In the fourth step, the remaining studies were pooled, and the book chapters, theses, and short articles were removed. For withdrawing the short articles, a criterion of at least five pages was used, and some articles with fewer were kept since they presented some desirable characteristics, such as related works and final results. Finally, some studies not related to this research

1 https://dl.acm.org/.
2 https://scholar.google.com.br/.
3 https://ieeexplore.ieee.org/Xplore/home.jsp.
4 http://digital-library.theiet.org/.
5 http://jmirpublications.com/.
6 https://www.ncbi.nlm.nih.gov/pubmed/.
7 https://www.sciencedirect.com/.
8 https://link.springer.com/.
9 http://isiknowledge.com.
10 https://onlinelibrary.wiley.com/.

Table 2 Quality assessment items

Section	Description
Criteria 1	The article has a research proposal
Criteria 2	The article presents a literature review
Criteria 3	The article discusses related work
Criteria 4	The article has a methodology
Criteria 5	The article presents results
Criteria 6	The article has a conclusion
Criteria 7	The article suggests future research

Table 3 Review articles related to the research questions

Section	Description	Research questions
Open content		
	Title	RQ4, RQ5
	Abstract	RQ1, RQ3, RQ5
	Keywords	RQ1, RQ3, RQ4, RQ5
Article content		
	Introduction	All questions
	Method	All questions
	Results	All questions
	Discussion	All questions
	Conclusion	All questions

remained. We looked at the full text to remove those that were not relevant.

2.5 Quality assessment

One of the concerns of this review is to assess the quality of the selected corpus. According to [32], the quality criterion verifies whether the article is a significant study. Therefore, questions were elaborated, which were used as criteria to evaluate the articles found. According to Table 2, the presence of the following items in each article was verified: the research proposal, literature review, related works, methods, results, conclusions, and future work.

2.6 Data extraction

The data extraction and synthesis were performed by reading each of the articles included in the review and by extracting the relevant data. This was managed through the Mendeley bibliographic management tool and spreadsheet software. To keep the information consistent, the data extraction for the studies included in the review was based on the research questions and where they were answered within the body of the article, as can be seen in Table 3. To synthesize the data, we inspected the extracted data for similarities. The results of the synthesis will be described in the subsequent sections.

3 Results

In this section, we present the results of the studies evaluated, related to the research theme. In the following subsections, we attempt to answer each proposed research question by synthesizing the information. As a result, in addition to answering the research questions, contributions are also suggested in the field of the use of context-aware data in the health field, with a proposed taxonomy and an updated view of the main challenges.

3.1 Strategy for conducting the search

For this research, we chose ten electronic databases (listed in Sect. 2.3) from which to select the articles. The criteria for choosing these databases were their coverage of the fields of computer science and healthcare. For the selection of articles in each database, we used a few procedures to limit our search by selecting articles in English, in the period from 2008 through 2018, and excluding results from patents and citations.

3.2 Proceeding with the article selection

Our search process is presented in detail in Fig. 1, showing the processes of exclusion and filtering.

Initially, our search string found 3826 articles in the different databases. After the initial outcome, we used the criterion of removal of impurities, which consists of the removal of articles that were published in journals and conferences unrelated to the topic of this research, and the removal of duplicate articles, with 724 studies remaining. After the first filter, we used the title and the article abstract as an exclusion criterion. Studies in which the titles or abstract did not contain words related to the subject of this study, such as health, context, aware (especially words that are in the search chain), were excluded from the corpus, leaving 154 articles that were grouped to apply new criteria of exclusion.

After grouping the articles, the exclusion criteria applied were the removal of chapters from books, theses, and short articles, with 79 articles remaining. The criterion for short articles was used to eliminate articles with five or fewer pages, except articles that presented proposals of architectures and presented final results.

In the remaining 79 articles, an analysis was performed, and the articles that did not contribute significantly to the criteria used in this research were eliminated. In addition, some of these studies belonged to the same group of researchers, presenting the same methods or techniques,

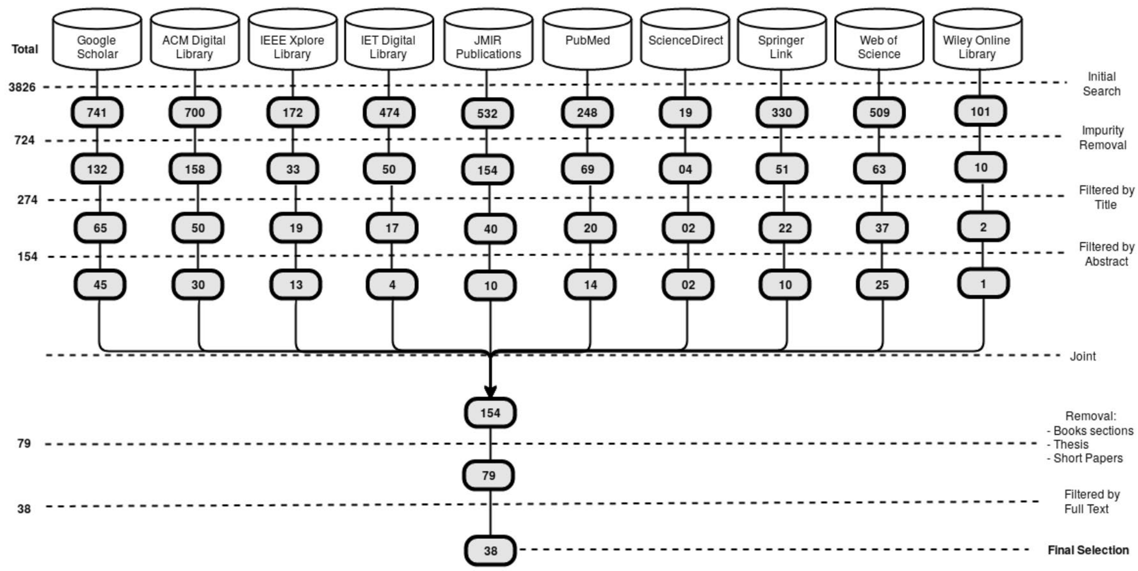

Fig. 1 Articles selected by database

from which only the most representative articles were selected. Thus, 38 articles were selected as the basis for this study. An overview of the selected studies is presented in Table 4, showing the identifier, reference, year of publication, publisher, and type.

3.3 Assessing the quality

In this section, we present a qualitative analysis of the articles, based on the criteria defined in Sect. 2.5. We used a scale from 0 to 7 as in Roehrs [55] to analyze and classify these articles, described in Table 2, with 31 articles (81%) covering five or more of the cited criteria and 7 articles covering four of the quality criteria.

Regarding the year of publication, the distribution of articles is shown in Fig. 2, of which 26 articles of the corpus were published in the last five years.

Figure 3 shows the distribution of the number of citations per article. From the figure, it is possible to perceive that articles that do not have citations are mostly from the year 2018. On the other hand, the articles most cited (more than 30) were published, for the most part, in recent years. The remaining articles have, in their majority, more than eight citations.

4 Answers to the Questions and Discussion

This section focuses on the research questions defined in Sect. 2.2 to review the results of the literature review and gain some insight. The literature researched discusses various definitions and classifications, which are presented and discussed below.

4.1 How is the use of context awareness in the health field defined and classified in existing research?

The answer to question RQ1 leads to the definition of a taxonomy based on the analysis of the current studies. This taxonomy is illustrated in Fig. 4 and is based on observations about the technologies, methods of use, and target problems. Sometimes, the proposals combine various techniques. As a result, the classes in this taxonomy are not mutually exclusive, and each study can be inserted into one or more of them. The process of defining the taxonomy began with an analysis of all the articles of the corpus to identify patterns, characteristics, and categories. Moreover, we defined five central concepts to analyze (1) sensors, (2) scenarios, (3) context modeling, (4) fusion methods, and (5) context reasoning.

The first element refers to the sensors, which were classified into three types: physical, virtual, and logical. Physical sensors were separated in the taxonomy into embedded sensors (subdivided into wearable and internal/smartphones) and external sensors. Physical sensors appear to evaluate activities, as Mshali, Lemlouma and Magoni [43], who use location sensors (GPS) and environmental sensors (humidity, temperature, camera) to monitor orientation and memory activities in the elderly living alone. Another way to use physical sensors, this time using an accelerometer, is to encourage a more active lifestyle by promoting physical exercise [4]. Unlike physical sensors, virtual sensors do not

Table 4 Articles related to the research questions

Identifier	Year	Author	Publisher	Type
[8]	2018	Baloch, Shaikh and Unar	Springer	Journal
[43]	2018	Haider, Tayeb and Damien	Elsevier	Journal
[44]	2018	Mshali et al.	Elsevier	Journal
[46]	2018	Newcombe et al.	IEEE	Conference
[3]	2017	Alirezaie et al.	MDPI	Journal
[6]	2017	Azimi et al.	Springer	Journal
[26]	2017	Gomes et al.	Wiley	Journal
[31]	2017	Jung	MDPI	Journal
[38]	2017	Michalakis and Caridakis	Springer	Journal
[36]	2016	Matthew-Maich et al.	JMIR	Journal
[58]	2016	Santos et al.	Springer	Journal
[13]	2015	Chiang and Wen-Hua	Springer	Journal
[17]	2015	Deen	Springer	Journal
[19]	2015	Dobrescu	Inase	Journal
[21]	2015	Elmalaki, et al.	ACM	Journal
[24]	2015	Forkan et al.	IEEE	Journal
[27]	2015	Hameurlaine et al.	Springer	Journal
[34]	2015	Kuijs, Rosencrantz, and Reich	Iaria	Conference
[4]	2014	Alshurafa et al.	IEEE	Journal
[9]	2014	Beattie et al.	ACM	Journal
[12]	2014	Cherkaoui and Agoulmine	IEEE	Journal
[37]	2014	Mcheick	Elsevier	Journal
[57]	2014	Sannino and De Pietro	Scopus	Journal
[61]	2014	Thomas et al.	Inderscience	Journal
[64]	2014	Zerkouk et al.	Springer	Journal
[35]	2013	Machado et al.	Springer	Conference
[41]	2012	Mnatsakanyan et al.	Elsevier	Journal
[45]	2012	Nava-Muñhoz and Morán	MDPI	Journal
[47]	2012	O'Donoghue and Herbert	ACM	Journal
[56]	2012	Sanchez-Pi and Carb	Springer	Journal
[59]	2012	Song et al.	Taylor & Francis	Conference
[7]	2012	Wan D. Bae et al.	IEEE	Conference
[40]	2011	Mitchell et al.	IEEE	Journal
[62]	2010	Trebatoski et al.	Journals@UIC	Journal
[2]	2009	Al-Neyadi and Abawajy	Springer	Conference
[20]	2009	ElHelw et al.	IEEE	Conference
[39]	2009	Mileo et al.	Oxford	Journal
[33]	2008	Komnakos et al.	ACM	Journal

generate data by themselves, but retrieve data from different sources and publish it as sensor data. Logical sensors produce useful information through the combination of physical and virtual sensors (e.g., a calendar). In Sannino and De Pietro [57], accelerometer and ambient temperature data (physical) are combined with location data and (virtual) maps to indicate the location in risk situations.

The second element of the taxonomy concerns the scenarios in which the data collected and the context can aid in healthcare. Some researchers have proposed middleware for ambient assisted living [26], increasing the degree of independence and mobility for the elderly or people with chronic illnesses. Chiang and Liang [13] propose an intelligent home care system, which is also applied to the elderly and to patients with chronic illnesses. Mshali, Lemlouma and Magoni [43] suggest an adaptive e-health system for smart homes, able to detect behavioral changes, focusing on the elderly and people living alone. Already, Nava-Muñhoz and Morán [45] report the lack of awareness about the situations that involve care for the elderly and the lack of information about the availability of caregivers in a nursing home, proposing a context-aware notification model.

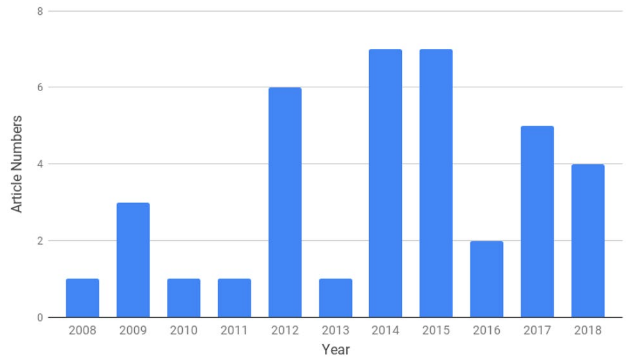

Fig. 2 Number of papers by year of publication

The fourth and fifth elements of the taxonomy refer to context reasoning. This element includes data fusion and reasoning techniques. Hameurlaine et al. [27] propose a rule-based model for reasoning about contextual information to provide appropriate services in U-Healthcare systems. Similarly, Mileo et al. [39] use a reasoning component that applies logical rules intended for the correct interpretation of incomplete or inconsistent contextual information applied to home healthcare. Alshurafa et al. [4] use an unsupervised technique for clustering in the proposal of a health-oriented physical activity recognition framework using wearables. ElHelw et al. [20] propose a statistical method for merging information from environmental sensors and wearables applied in a framework for pervasive healthcare monitoring and use a probabilistic technique for context reasoning. Mnatsakanyan et al. [41] propose a model of distributed information fusion based on Bayesian networks, applied to regional public health surveillance.

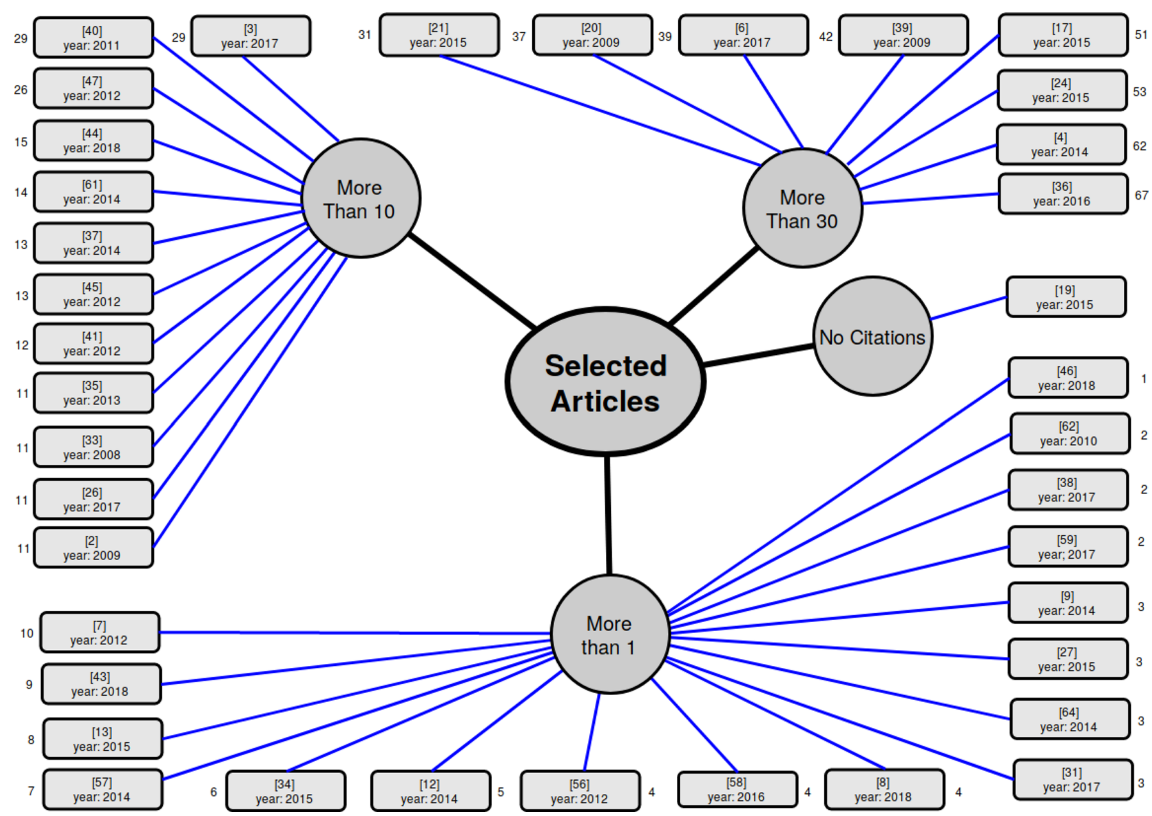

Fig. 3 Number of citations per article

The third element of taxonomy refers to context modeling. Data must be modeled and represented according to its meaning. For this, different techniques are used. Bae, Alkobaisi, and Narayanappa [7] propose a framework of data analysis to support environmental health decisions, with context modeling based on ontology. Alirezaie et al. [3] present a system for smart homes, also with a context modeling technique based on ontology. Mcheick [37] proposes a hybrid form for context modeling, using an object-based approach and XML (markup scheme).

4.2 What are the challenges related to the use of context-aware information in healthcare?

To answer question RQ2, we list and identify common challenges in using context-aware data in healthcare. The

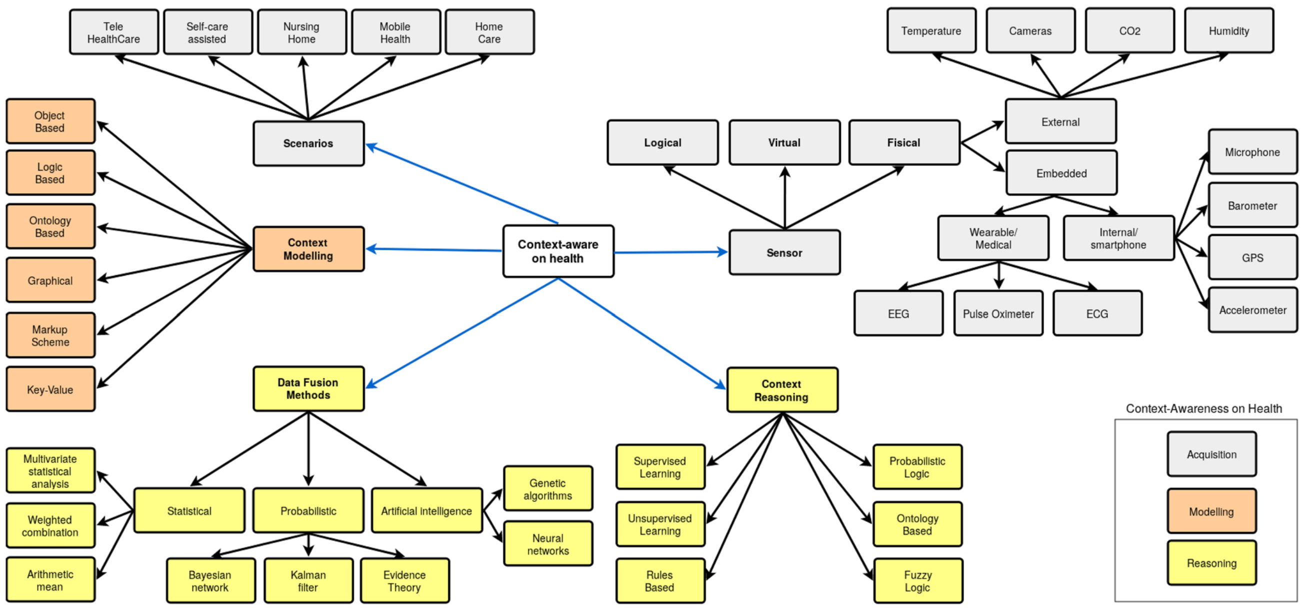

Fig. 4 Taxonomy of the use of context awareness in healthcare

Table 5 Challenges and concerns

Challenge	Reference article
Heterogeneous technologies: data integration/data fusion	[3, 6–8, 13, 17, 19, 20, 26, 34, 39, 41, 43, 44, 47]
Reliable communication: different wired and wireless technologies	[3, 7, 12, 17, 19, 20, 26, 33, 36, 38, 39, 44, 45, 47, 58, 59, 64]
Power management: power consumption	[3, 8, 12, 17, 20, 21, 24, 26, 33, 40, 44, 47, 61]
Scalability: reasoning and inference functionalities	[3, 7, 8, 20, 26, 34, 44]
Accuracy: data, monitoring	[7, 8, 20, 24, 33, 34, 38–40, 43–47, 56, 57, 61, 64]
Security: availability, privacy, confidentiality, etc.	[2, 3, 8, 24, 31, 34, 36, 38, 44, 58, 64]

problems are grouped in Table 5. As can be seen, the content brings together some common characteristics of challenges related to the use of heterogeneous technologies, challenges associated with the aspects of communication, energy management, scalability, and security.

The first and second lines of Table 5 deal with heterogeneous technologies and trusted communication. Gomes et al. [26] point to the need for a software infrastructure flexible enough to interact with different types of sensors and actuators, and with hardware and communication technologies of different formats. We should take into consideration that the data packets of different sensors can have different formats and encodings, increasing the need for transcoding modules that encapsulate the logic needed to interpret the data exchanged [20].

The third line of Table 5, power management, refers to the power consumption problem in the sensors. Assuming that most sensors do not have a permanent source of energy, depending on batteries for their power source, power consumption becomes crucial for sensors used in environmental and health contexts [26]. In addition, the use of different transmission technologies (Zigbee, Bluetooth, WiFi) with different transmission consumption needs makes power management a significant challenge in this scenario. For this, Alirezaie et al. [3] make extensive use of state-of-the-art communication protocols in a context-aware system based on ontology for intelligent houses, seeking a robust communication between IoT devices, but efficient in terms of consumption.

The fourth and fifth lines of Table 5, scalability and precision, are related, in the case of scalability, to the capacity to attend to a varied and increasing number of sensors and, in this case, to attend to the increased processing related to the generated data [26, 44]. In turn, accuracy and reliability are perceived as critical issues in context-aware applications. Sometimes, wearable sensors do not provide enough information to build the situation, so additional sensors are needed. Baloch, Shaikh, and Unar [8] propose a three-tiered health-IoT data fusion approach, which includes, in one of them, context-aware data fusion,

Table 6 Scenarios

Scenario	Reference article
Home care	[3, 6, 17, 27, 31, 33, 35, 36, 39, 45, 47, 61]
Mobile health	[7, 9, 27, 33, 36, 38, 41, 47, 57, 59, 62]
Nursing home	[45]
Assisted auto care	[9, 40]
Tele-healthcare	[9, 13, 61]

combining vital sign data analysis and environment to prevent false alarms.

Finally, the sixth row of Table 5 refers to security. In health monitoring systems, security is a critical issue because it involves many processes and components: sensors and actuators, data collection, and communication. Michalakis and Caridakis [38] point out that people show greater sensitivity when sharing their personal health information, that is, privacy and security are of greater importance for health services compared to other similar services. Al-Neyadi and Abawajy [2] propose a mechanism to control access to e-health systems based on context. To ensure that services and information are accessed only by people who have the privileges to access them, it takes into account the person trying to access the data, the type of data being accessed, and the context of the transaction in which the access attempt is made.

4.3 What are the use case scenarios related to context awareness in healthcare?

The answer to question RQ3 defines the scenarios in which healthcare technologies are applied. These scenarios are shown in Table 6 and are based on the analysis of the studies that are part of the corpus treated in the present paper. Often, the same study presents more than one scenario of application, as can be seen in Table 6.

The first line of Table 6, home care, refers to the scenario defined by home healthcare. In this regard, several studies in the corpus of this article present different solutions. Mileo et al. [39] propose the use of an intelligent home health system characterized by a wireless sensor network (WSN) and a reasoning component based on the set of responses (ASP). Alirezaie et al. [3] use an ontology to integrate the measurements collected from heterogeneous sources to enable the semantic interpretation of events and context awareness, while Hameurlaine et al. [27] use an ontology to represent information about the context and a rule-based model to reason about this contextual information. Jung [31] presents a smart home technology using wearable sensors and environmental sensors, with the aim of creating an awareness of the situation and supporting decision-making and recommending appropriate treatment based on one health risk ratio.

The second line of Table 6, mobile health, refers to the ability of systems to adapt health monitoring in the face of patient mobility. In this context, Komnakos et al. [33] present a study on the potential and performance evaluation of 3.5G technology to provide comprehensive electronic health applications, considering the performance of the sensor network together with the 3.5G network, a critical factor for this application. On the other hand, Bae et al. [7], taking into consideration the negative health effects of environmental factors, such as air pollution and humidity, propose the monitoring of individual movement trajectories and environmental conditions, to identify significant relations between these data as a way of supporting public health systems. Both Sannino and Pietro [57] and Komnakos et al. [33] point out that a knowledge of the patient's context is essential for application services in mobile health environments and uses. The former propose, to this end, a rule-based decision support system; the latter propose a scalable ontology for modeling and reasoning.

For the third row of Table 6, according to Nava-Muñhoz and Morán [45], there are two significant problems in the care of the elderly in a nursing home, taking into account the criticality of this type of environment. First, there is a lack of awareness about situations involving care of the elderly, and second, the lack of information about the availability and activities of other caregivers to support the process of coordination. To deal with this kind of situation, they propose a model for the design of context-sensitive notifications in critical environments, having as the main characteristic that it considers three context sources (the environment, the sender, and the recipient of the notification).

Regarding assisted self-care and telehealthcare, the fourth and fifth lines of Table 6, respectively, refer to self-care assisted through the application of digital technologies. In Beatti et al. [9], regarding persons suffering from chronic obstructive pulmonary disease, it is pointed out that the continuous monitoring of a patient's health, behavior, and contextual information provides the ability to detect a decline in their health before a problem occurs. They propose a context-aware self-management tool with a prediction module to generate appropriate intervention warnings, informing the patient that their health status is declining. Chiang and Liang [13] and Mitchell et al. [40] propose a home care system that stores the required contexts of knowledge in ontologies, including the physiological information and the patient's environmental information, providing a unified query interface with the contextual data on mobile devices and providing interactive user feedback.

4.4 What are the context modeling techniques employed in healthcare?

To answer question RQ4, we discuss the most popular context modeling techniques. Each of the following methods has its strengths and weaknesses, and the actual implementations of these techniques may vary, depending on the application domain.

According to Mshali et al. [44], the key-value modeling technique models information as key-value pairs in different formats, but is not scalable and is unsuitable for storing complex data structures. Another technique, using a markup scheme, defines hierarchical data structures using a markup language, such as XML. Marking tags are used to represent the data format. Graphical modeling consists of a diagrammatic representation of contextual data at the design level, using appropriate models, such as the UML and others. Object-oriented modeling uses the concept of objects, with class and relationship hierarchies, employs encapsulation, reusability, and inheritance to represent context data. In logic-based modeling, context is represented as a set of facts, expressions, and logical rules. Ontology-based modeling represents knowledge and contextual information using semantic technologies. Different reasoning and standardization (RDF, OWL) capabilities are available.

Mileo et al. [39] present an intelligent home system with a reasoning component based on the set of responses (ASP), responsible for the continuous contextualization of the patient's physical, mental, and social state. The reasoning component applies expressive logical rules that aim at the correct interpretation of incomplete or inconsistent contextual information. Chiang and Liang [13] and Kuijs, Rosencrantz and Reich [34] use ontologies for storing contexts, environmental information, and information about the patient. Alirezaie et al. [3] and Hameurlaine et al. [27] determine the potential of intelligent home environments and propose the use of scalable ontologies for modeling and reasoning, not only about patients' health measurements but also about all the contextual information, so as to provide appropriate health services in smart homes.

Mcheick [37] states that to model the context of an application, one must first look for the different elements that affect the application, in order to infer contextual elements. Thus, the context construction is divided into two types of features: dynamic ones (medical and environmental data) that change frequently, and static elements (name, age, medical condition). A hybrid form for context modeling is proposed, which is object-based for the dynamic components but uses XML (a markup scheme for the static elements).

Table 7 Fusion and reasoning methods

Methods	*Reference articles*
Data	
Statistical	[20, 31, 43]
Fusion	
Probabilistic	[7, 9, 17, 20, 41, 45, 59]
Supervised learning	[24, 40]
Unsupervised learning	[4]
Context	
Rules based	[2, 9, 19, 24, 27, 39, 57, 58]
Reasoning	
Probabilistic logic	[9, 20]
Ontology based	[3, 34, 64]
Fuzzy logic	[13]

4.5 What are the methods of reasoning and fusion of data used in context-sensitive information in health?

In question RQ5, we present and discuss the fusion techniques used to extract significant data from different IoT sensors, as well as present the methods of contextual reasoning that appear in the articles in the corpus. The characteristics of contextual information make it difficult to give it a precise meaning: Substantial amounts of data are required to understand the user's intentions and situations. Also, medical services require precision. To this end, data from various sources and sensors are combined in order to obtain a more reliable, accurate, and complete result. These data are used to support reasoning components. Using context information, the behavior of the application can be customized to a specific situation [8, 27]. The methods are presented in Table 7 and are based on the analysis of the studies that are part of the corpus. Often, the same study employs more than one method, as can be seen in the table.

According to Alshurafa et al. [4], the detection of human activity independently of its intensity is essential in many applications, especially in the calculation of equivalent metabolic rates and the extraction of consciousness from the human context. For this purpose, they use *k*-means exclusive clustering and a probabilistic clustering algorithm based on a Gaussian mixture model. Alirezaie et al. [3] focus on using ontologies to integrate the measurements collected from heterogeneous sources, in order to enable a semantic interpretation of events and context awareness. The reasoning component uses a solution based on answer set programming. Likewise, Hameurlaine et al. [27] propose a scalable ontology for the integration of data from different origins, as well as a rule-based reasoning component. Sannino and De Pietro [57] also propose an intelligent mobile system that automatically recognizes the context, analyzing data from

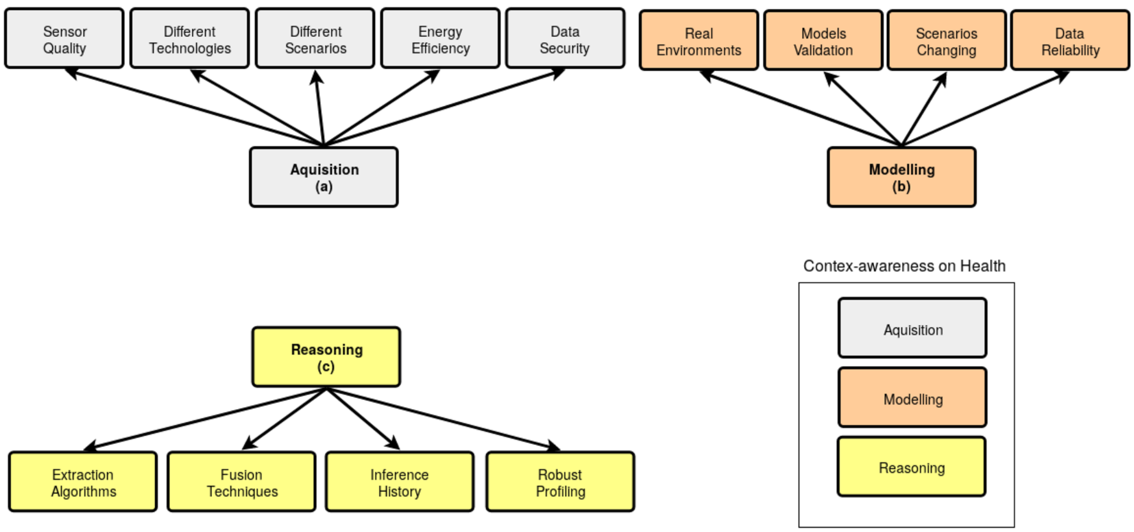

Fig. 5 Summary of challenges

various sensors and automatically choosing, through a rule-based decision support system, the action to be performed.

Chiang and Liang [13] develop an ontology-based healthcare system for storing contexts, with a fuzzy inference mechanism for decision-making. Song et al. [59] propose a context-aware middleware for mobile health services, specifically for preventive medicine. The middleware collects the information through the recognition of diverse environmental data that affect the patients' health.

Bayesian probability has also been applied to the calculation of repetitive frequency values in the environmental and personal information of the user to determine the relations between the context information and preventive medicine practices. For example, Forkan et al. [24] present a two-stage learning methodology, that correlates contextual attributes with limit values of vital signs, generating at the end a set of association rules specific to a given patient: A supervised learning system is applied to the dataset generated in the first step, thus improving the accuracy of predicting the patient's situation. Mitchell et al. [40] present a framework for queries on the mobile device with a supervised learning component.

5 Challenges and Future Directions

After answering all the research questions, we can identify the challenges inherent in the use of context data in healthcare. Starting from the taxonomy, we highlight the challenges in Figure 5. The first challenges are (a) context acquisition (including sensors and application scenarios). [26] addresses sensors concerning their quality and improvement in the provided context data. [33] provides a comparison between various low- and high-rate sensor technologies (e.g., Zigbee vs. Bluetooth) in different scenarios and with different quantities including patient movement, as a way to make a home care platform more effective. Other challenges to data acquisition include energy efficiency, responsiveness, and robustness. Since sensors often report their data to a central node, there is a need for secure protocols. The standardization and integration of sensors is desirable and presents itself as another challenge [17, 38], in addition to extending the existing models to different scenarios, as a form of validation.

With respect to context (b) modeling, the reliability and integrity of the provided data are essential, with no room for data provision gaps. Otherwise, there will be poor representation of context awareness [26]. For [13], domain experts could provide more accurate knowledge, to enrich the knowledge ontologies of the user context. The exchange of scenarios performed by the patient can cause multiple difficulties in the construction of the new context and its representation according to [24]. Just as the validation of contextual representation models should be extended with added data, to better represent reality [4, 64], the expansion of prototypes for real physical environments is pointed to by [35] as something to be achieved.

From the perspective of (c) reasoning, which involves context reasoning and data fusion methods, some challenges arise. These include the development of algorithms for the extraction and combination of visual information and improved data fusion techniques for more accurate detection of activities, avoiding false alarms [3, 20]. The graphical representation of dependencies and results of reasoning tasks can be improved through automatic methods applied to the analysis of the history of the inferences, according to [39]. More robust methods of profiling autonomic behavior, which will improve the detection of activities, would minimize the workload of caregivers, making possible the long-term monitoring of the elderly [20, 45].

To conclude, we can cite the challenges and issues of security and privacy, regarding the use of context information in health. These issues directly affect the trust in systems that use information generated by sensors to create a contextual perception [64] [34]. At this point, we can highlight acceptance as an important challenge in the use of sensors, especially in what refers to the reliability in the use of intelligent medical systems at home [66], or the ethical and morally justified use of the technology, as discussed in [29]. In [30], there is a discussion of the acceptance of new technologies in light of usability and accessibility engineering, concerning their development and use. Likewise, the use of cloud computing for intense computing procedures and the insecurity of people with regards to the sharing of their personal medical data poses challenges to be overcome concerning data security and privacy [38]. Finally, access to patient information by third parties should be carefully controlled, incorporating trusted domains so that unknown users who are not part of the domain do not have access [2].

6 Conclusions

This study aimed to raise and discuss the main issues related to context awareness in healthcare, and to identify the concepts and technologies in this field. To answer the research questions, we first sought to systematize and qualify the information that served as the source for the research. To conclude the paper, we have identified and proposed a taxonomy for the scope of the research, which was created following an analysis of the relevant articles published over the last decade. In the taxonomy, we were able to identify and group various scenarios and classifications for context-aware information in healthcare, from "Data Fusion Methods" and "Scenarios" to "Context Reasoning" and "Data Fusion" approaches. By establishing the taxonomy, it was possible to observe other relations essential to understanding the context-aware information, perceiving aspects concerning concerns and challenges. We have identified several approaches for applications in different scenarios and using different types of sensors, including their limitations. The difficulty in mapping the patient's context from different scenarios and sensors, using different communication protocols, leads to a difficulty of precision in the definition of the patient's context awareness. Thus, different methods were also analyzed for data fusion and different reasoning techniques.

This research has been limited to aspects of context-aware health use, not including the use of context information in other domains, for example. In this sense, the review focused exclusively on articles that addressed the basic concepts of context awareness of health data. This research sought to answer the research questions that formed proposals to obtain a sketch of the current literature related to this subject, without specifically evaluating any framework or computerized system that refers to the use of context awareness using health data. The research was limited to obtaining articles published in several scientific portals related to ICT and health, limited to studies found in these sites when we implemented the steps of the methodology of a systematic review of the literature. We focused our work on scientific articles and have not considered commercial solutions or more technological approaches.

In future studies, we envision a focus on security, privacy, and trust issues and challenges that directly affect the trust in the use of context-aware health data. Although challenges related to these issues have been around for a quite some time, they still do not have definitive answers. Other aspects that can be studied that are important for context awareness in health include the standardization and integration of sensors from different manufacturers, using different communication protocols and transmission technologies, improving the representation of the consciousness of the contexts through a more accurate knowledge of the environments and contexts of application, and the development of new algorithms for context reasoning and data fusion, aiming at a more precise detection of activities.

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