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Semantic Technologies in Sensor-Based Personal Health Monitoring Systems: A Systematic Mapping Study

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Abstract. In recent years, there has been an increased focus on early detection, prevention, and prediction of diseases. This, together with advances in sensor technology and the Internet of Things, has led to accelerated efforts in the development of personal health monitoring systems. Semantic technologies have emerged as an effective way to not only deal with the issue of interoperability associated with heterogeneous health sensor data, but also to represent expert health knowledge to support complex reasoning required for decision-making. This study evaluates the state of the art in the use of semantic technologies in sensor-based personal health monitoring systems. Using a systematic approach, a total of 40 systems representing the state of the art in the field are analysed. Through this analysis, six key challenges that such systems must overcome for optimal and effective health monitoring are identified: interoperability, context awareness, situation detection, situation prediction, decision support, and uncertainty handling. The study critically evaluates the extent to which these systems incorporate semantic technologies to deal with these challenges and identifies the prominent architectures, system development and evaluation methodologies that are used. The study provides a comprehensive mapping of the field, identifies inadequacies in the state of the art, and provides recommendations for future research directions.

Keywords: semantic technologies, ontologies, linked data, knowledge graphs, sensors, Internet of Things, health monitoring

1. Introduction

Non-communicable diseases are on the rise globally, resulting not only in decreased quality of life but also increasing healthcare costs [1]. For this reason, there have been accelerated efforts to develop personal health monitoring systems for early detection, prediction, and prevention of diseases. The emerging paradigm of precision health goes beyond treating existing diseases and rather focuses on preventing disease before it strikes [2]. Eschewing the one-size-fits-all approach in favour of assessing individual circumstances, precision health encourages people to actively monitor and work towards improving their health so as to lower the risk of disease [3]. Personal health monitoring is part of this vision, allowing people to not only increase understanding of their health but also to receive recommendations for any necessary interventions. Significant advances in the Internet of Things (IoT) over the last decade has led to the rapid rise of wearable sensors, which are increasingly being used for health monitoring outside traditional clinical settings. Wearable sensors can collect and measure physiological data, including biosignals such as electrocardiogram and photoplethysmography data, and vital signs such as heart

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rate, blood pressure, and blood oxygen saturation. Additionally, ambient sensors can monitor environmental factors such as air quality and weather, which have a significant impact on health.

There are several crucial issues arising from the use of multiple sensors for health monitoring. The first of these interoperability. Heterogeneous sensor observations, different data transmission technologies and standards for describing health data all contribute to interoperability issues in personal health monitoring systems. Secondly, the representation of health domain knowledge and its integration with sensor data remains a challenging task [4]. By its nature, sensor data is dynamic and complex, necessitating interpretation into higher-level concepts or situations [5]. Situation analysis involves the use sensor data to detect the current state of a given environment (situation detection), while anticipating possible future states (situation prediction) [6]. The representation of domain knowledge is essential for facilitating situation analysis from sensor data and supporting subsequent decision-making, while taking an individual's context into consideration. Dey and Abowd [7] define context as any information that can be used to characterize the situation of an entity, including location, identity, activity, and time. Such information is essential for accurate situation analysis. Thirdly, health outcomes are probabilistic, resulting in inherent uncertainty in the decision-making process [8]. Additionally, uncertainty can arise in sensor data due to sensor faults, noise, and ambiguous observations.

Semantic technologies have emerged as a promising way to alleviate these issues. Semantics is concerned with the meaning of language, and is critical for ensuring interoperability and the unambiguous representation of domain knowledge. Additionally, semantics enables reasoning, allowing systems to derive higher-level knowledge and insights from sensor data [9]. The Semantic Web, first envisioned by Berners-Lee et al. [10], is an enhancement of the current World Wide Web that makes its data readable and understandable by humans as well as machines, including sensor-based devices [11, 12]. The Semantic Web has given rise to a number of technologies that provide meaning to data, making it accessible and useful. The goal of this study is to systematically map the state of the art in the use of these semantic technologies in sensor-based personal health monitoring systems. The contributions of this paper are as follows:

1. A **systematic mapping** of the field is presented based on 40 systems that are systematically selected to represent the state of the art.
2. Through an analysis of these systems, **six key challenges** related to the use of sensors for personal health monitoring are identified: interoperability, context awareness, situation detection, situation prediction, decision support, and uncertainty handling. The extent to which these challenges are addressed by the systems is critically evaluated, and the role of semantic technologies in managing each challenge is discussed.
3. Following an analysis of the current architectures, components, and functionalities, a **reference layered architecture** is proposed to provide guidance for the design and development of new systems.
4. Inadequacies in existing systems and outstanding issues in the field are highlighted, and potential **directions for future research** are identified.

The remainder of this paper is structured as follows. Section 2 provides an overview of personal health monitoring using sensors and the challenges faced in this area, motivating the need for the integration of semantic technologies in health monitoring systems. The section then provides a background of semantic technologies and how they can enhance sensor-based health monitoring systems. Section 3, presents an overview of related reviews and surveys, motivating the importance of this study. Section 4 details the methodology used to conduct the study, including the search strategy and the inclusion and exclusion criteria, culminating in a summary of the systems. Section 5 introduces the six key challenges that such systems must address, and discusses and critically evaluates the systems according to this criteria. The system architectures are explored in Section 6, while Section 7 investigates the methodologies and evaluation approaches used in the different systems. Finally, Section 8 concludes the study by making recommendations for future research directions.

2. Background

2.1. Sensor-based Personal Health Monitoring

Sensors used for health monitoring are typically worn, implanted, or placed in close proximity to the human body. When several such sensors are used at the same time, they form a wireless body sensor network, also known as a body area network [13]. This is part of the IoT paradigm, in which sensor-based "things" connect and exchange data over a shared network such as the Internet. Two categories of physiological data can be collected from health monitoring sensors: vital signs and biological signals (biosignals). The primary vital signs are heart rate, blood pressure, respiratory rate, temperature, and blood oxygen saturation [14]. Biosignals are space- or time-based records produced from electrical, chemical, or mechanical activity within the body during a biological event such as a beating heart [15]. They include records of electrical activity in the body such as electrocardiograms (ECG), electromyograms (EMG), and electroencephalograms (EEG), as well as optical signals from photoplethysmography (PPG).

Health monitoring sensors are generally either wearable or implantable. Wearable sensors are worn on the body or are otherwise integrated with clothes and shoes. Such sensors include electrodes for measuring electrical signals, thermal sensors for measuring temperature, and PPG sensors. Smart watches and bands are the most commonly used wearable sensors, but earables (devices placed in the ear) have recently emerged as a promising alternative [16, 17]. In contrast, implantable sensors operate from within the human body. Although they are much less commonly used than wearable sensors, they are particularly useful for monitoring chronic illness as well as post-surgery monitoring to minimise complications and avoid readmission [18]. Health monitoring sensors also include portable devices that can measure physiological data but cannot be practically worn or used for prolonged periods of time. Examples of these include blood pressure monitors and pulse oximeters. Additionally, ambient sensors are increasingly being incorporated in health monitoring to monitor the state of the external environment, such as temperature, humidity, and air quality.

The use of multiple sensors can hinder interoperability in personal health monitoring systems due to the heterogeneity of sensor devices, observation data, and measurement procedures [19]. Additionally, such systems need to incorporate data from non-sensor sources such as electronic health records and hospital information systems, which use different frameworks and standards to describe health data. Sensor data also tends to be dynamic and complex. This is particularly true of physiological data in the health domain, which requires expert knowledge to interpret and analyse. Furthermore, sensor data can contribute to uncertainty in situation analysis and decision support. Uncertainty can arise when the sensor observation is ambiguous, when all the relevant attributes cannot be measured, when there is impreciseness and noise, or when the degree of confidence about what is represented by the data is less than 100% [20, 21]. These challenges can be addressed by the incorporation of semantic technologies.

2.2. Semantic Technologies for Sensor Data and the Health Domain

Three semantic technologies have emerged as the most prominent over the years [12]: ontologies, knowledge graphs, and linked data. Ontologies are a powerful modelling tool that have been widely used for reasoning and representation in sensor-based systems [5]. A knowledge graph is a graph-based data model capable of capturing real-world knowledge, with its nodes representing entities of interest and its edges representing relations between them [22]. Linked data is a set of best practices for publishing and connecting structured data on the Web [23]. It should be noted that there is significant overlap between the three technologies and that they can be used in conjunction. For instance, ontologies can be classified as a type of knowledge graph [22] or a component of one [24], and both knowledge graphs and ontologies can be published using a linked data approach [12]. Each of these technologies is discussed in greater detail in the remainder of this subsection.

The development of semantic technologies is facilitated using different languages and standards. The most well-known among the Semantic Web community are: Resource Description Framework (RDF)[1], a standard for

[1] https://www.w3.org/RDF/

the description and exchange of interconnected data; RDF Schema (RDFS)[2], which provides a vocabulary to enrich RDF data; Web Ontology Language (OWL)[3], a language for constructing ontologies; Semantic Web Rule Language (SWRL)[4], a language for expressing rules and logic; and SPARQL Protocol and RDF Query Language (SPARQL)[5], a language for retrieving and manipulating RDF data.

2.2.1. Ontologies

Arguably, the key technology underpinning the Semantic Web is ontologies. They can represent knowledge in a computational model that is machine readable and unambiguous, highlighting important concepts and relations in a particular domain [25]. This not only enhances interoperability but is also useful in capturing the domain knowledge necessary for situation analysis and subsequent decision support. There are generally three types of ontologies [26]. Top-level or foundational ontologies describe general concepts at an abstract level that can be reused independent of the domain. An example is the Basic Formal Ontology[6]. Domain and task ontologies describe concepts related to a generic domain (for example, health) or task (for example, diagnosis). Finally, application ontologies describe concepts related to both a specific domain and task. Such ontologies are developed for a specific application, and can be used in reasoning engines or software systems [25], including personal health monitoring systems. The remainder of this subsection provides an overview of existing ontologies that can support the development of sensor-based personal health monitoring systems.

Ontologies for Sensors

Several ontologies for sensors have been proposed in the literature. An early example is OntoSensor, a prototype sensor ontology proposed by Russomanno et al. [27] as a repository of sensor knowledge. OntoSensor is based on concepts from the SensorML standard and IEEE's Suggested Upper Merged Ontology (SUMO) [28]. Another sensor ontology is the Smart Applications REFerence ontology (SAREF)[7] [29] developed for IoT applications. The ontology describes devices and their measurements, services, tasks, properties, and states. There have been several extensions proposed for SAREF, including SAREF4ehaw[8] for eHealth and ageing well, SAREF4wear[9] for wearable devices, and SAREF4health [30] for use cases related to ECG data. One of the most well-known sensor ontologies is the semantic sensor network (SSN) ontology [19], which describes sensors and their capabilities, measurement processes, observations, and deployments. It was originally based on the Stimulus–Sensor–Observation (SSO) design pattern. Later, the Sensor, Observation, Sample, and Actuator (SOSA) ontology [31] was developed to replace the SSO pattern and provide a lightweight, user-friendly, and extendable core to the SSN ontology.

While these ontologies on their own are insufficient for the analysis of sensor data, they support the description of sensors and their observations, which is critical in any sensor-based system. Sensor ontologies can be extended to enrich the sensor data with spatial, temporal, and domain-specific metadata [32, 33]. Additionally, the use of ontologies for sensor data fusion, i.e. the combination of data from different sensors, has been explored in a number of domains and tasks, including military [34] and activity recognition [35] applications.

Ontologies in the Health Domain

The health domain is characterised by an extensive language and vocabulary, with specific terminology to describe anatomy, diseases, procedures, and beyond. Recognising the need for a standardised nomenclature, there have been several efforts to consolidate various healthcare concepts into a reference terminological resource. The Read Codes, a clinical classification code system, was developed and widely used in the 1980s [36]. The system was later refined as part of the Clinical Terms project, resulting in the third version of the Read Codes, also referred to as Clinical Terms Version 3 (CTV3) [36, 37]. The Systematized Nomenclature of Human and Veterinary Medicine Reference

[2]https://www.w3.org/wiki/RDFS
[3]https://www.w3.org/OWL/
[4]https://www.w3.org/Submission/SWRL/
[5]https://www.w3.org/TR/rdf-sparql-query/
[6]https://basic-formal-ontology.org/
[7]https://saref.etsi.org/
[8]https://saref.etsi.org/saref4ehaw/v1.1.1/
[9]https://saref.etsi.org/saref4wear/v1.1.1/

Terminology (SNOMED RT) [38] was introduced for the retrieval and analysis of clinical data. SNOMED RT and CTV3 were then merged to form SNOMED Clinical Terms (CT) [39], which is available as an ontology[10].

Besides SNOMED CT, there are other terminologies that hone in on specific aspects in the health domain. For example, Logical Observation Identifiers Names and Codes (LOINC) is a terminology for laboratory and clinical observations, while the International Classification of Diseases (ICD) [40], which is available as an ontology[11], focuses on classifying diseases, syndromes, and health-related phenomena [40]. For nursing and patient care, the International Classification for Nursing Practice (ICNP) provides a framework for the classification of nursing diagnoses, interventions, and outcomes [41]. Similar to the other classification systems, it is also available as an ontology[12]. Vital sign data and information can be modelled using the Vital Sign Ontology (VSO), which covers blood pressure, body temperature, respiratory rate, and pulse rate. [42].

Ontologies for Context Awareness

An important aspect of health monitoring is the ability to take context into consideration, which is critical for situation analysis. Consider a case where an individual's heart rate is suddenly elevated. If the individual is engaged in exercise, the increased heart rate is expected. However, if the individual is at rest, this could be a cause for alarm. Such contextual information can be represented using ontologies. For instance, OWL-Time[13] is an ontology that describes temporal properties of real-world objects, including sensors. The SWRL Temporal Ontology[14] can be used to model interval-based temporal information, while W3C Geo[15] provides a vocabulary for the representation of geospatial properties. Friend of a Friend (FOAF)[16] is an ontology that describes people and their activities, and can be useful in the creation of an individual's profile for health monitoring. Stevenson et al. [43] proposed Ontonym, a set of six upper ontologies for context-aware pervasive computing, with ontologies for time, location, people, sensing (representation of sensors), provenance (determining the origin of data), and events. Other context-aware ontologies are explored in detail in the reviews by Ye at al. [44] and Bajaj et al. [45].

2.2.2. *Linked Data*

Linked data typically refers to a set of RDF graphs linked using common identifiers, and in many cases, ontologies are used to inform the structure of the graphs [12]. When the emphasis is on free use, modification, and sharing, it is referred to as Linked Open Data [12, 46]. There are four principles for publishing linked data: firstly, uniform resource identifiers (URIs) must be used as names for things; secondly, HTTP URIs must be used so that people can look up those names; thirdly, useful information must be provided using standards such as RDF and SPARQL; and finally, links to other URIs must be included so that other useful resources can be discovered [23]. These principles allow for access to common vocabularies in the health domain, and can contribute to interoperability by ensuring heterogeneous health data is stored in a consistent format and structure. Linked data has been proposed for augmenting and representing sensor data in order to improve its accessibility and interoperability [47–49]. In the health domain, it has been explored in applications ranging from drug discovery [50, 51] to the representation of electronic health records [52, 53]. However, its use in health monitoring is not well explored in the literature, with few health monitoring systems incorporating a linked data approach.

2.2.3. *Knowledge Graphs*

Despite the relatively recent emergence of the term, Ehrlinger and Wöß [24] argue that knowledge graphs do not constitute a new technology but should rather be defined as a knowledge-based systems that integrate information into an ontology and apply a reasoner to derive new knowledge. The relationship between ontologies and knowledge graphs is also explored by Hogan et al. [22], who view ontologies as knowledge graphs with well defined meaning. Knowledge graphs can be represented as RDF graphs [46] and are typically published using a linked data approach. Regardless of its different definitions and representations, knowledge graphs have seen increasingly widespread

[10] https://bioportal.bioontology.org/ontologies/SNOMEDCT
[11] https://bioportal.bioontology.org/ontologies/ICD10
[12] https://bioportal.bioontology.org/ontologies/ICNP
[13] https://www.w3.org/TR/owl-time/
[14] https://github.com/protegeproject/swrlapi/wiki/SWRLTemporalOntology
[15] https://www.w3.org/2005/Incubator/geo/XGR-geo/
[16] http://xmlns.com/foaf/0.1/

use in the health domain. Previous research has explored the automatic construction of knowledge graphs from electronic health records [54, 55], which can then be used for clinical decision support. Knowledge graphs have also been proposed for health risk prediction [56], drug discovery [57], and as a tool for explainability in AI-driven health systems [58].

3. Related Reviews

Several reviews related to sensors, semantic technologies, and the health domain have been published. These reviews can generally be categorised into three overlapping groups, which are illustrated as a Venn diagram in Figure 1. The reviews in Group 1 focus on the use of semantic technologies in the health domain; those in Group 2 review the use of sensors and IoT in the health domain; and finally, those in Group 3 review the use of semantic technologies with sensor and IoT data. There is also a small group of other related reviews that do not fit into these three categories. All the related reviews are summarised in Table 1, and discussed in detail in the remainder of this section.

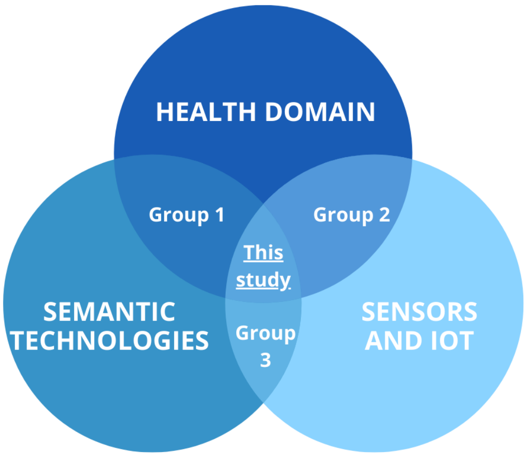

Fig. 1. Venn diagram illustrating the three focus areas of this study as well as the different groups of related reviews.

3.1. *Group 1: Semantic Technologies in the Health Domain*

Zenuni et al. [59] review the state of the art in the Semantic Web for healthcare, focusing on ontologies and semantic data repositories, including those published under linked data best practices. The authors consider several aspects of the health domain, including hospital systems, health vocabularies, and health datasets. A similar review is conducted by Haque et al. [60], who analyse the literature on Semantic Web applications for healthcare, exploring themes such as e-healthcare, disease diagnosis, information management, and the use of frontier technologies such as AI and IoT. In contrast, the review by Peng et al. [61] focuses on technologies used in health data integration for patient-centered health management. The authors investigate the aggregation of health data from various sources including wearable devices and health records, and propose Semantic Web technologies as an optimal approach for the integration of this data. Hammad et al. [62] survey semantic-based approaches for managing healthcare data, including data from wearable devices. The semantic techniques explored in this survey include Semantic Web languages and standards, ontologies, knowledge bases, and linked open data. Dimitrieski et al. [63] review ontologies and ontology alignment approaches in healthcare, highlighting the most prominent healthcare ontologies and exploring the ways in which existing ontologies, vocabularies, and taxonomies in the health domain can be aligned. Finally, the review by Jing et al. [64] focuses on the use of ontologies for rule management in clinical decision support systems. Although the reviews in this group provide a good overview of the ways in which semantic technologies have been used in the health domain, half of them do not mention sensors or IoT at all, while the other half do not include sensor data as a major focus.

3.2. Group 2: Sensors and IoT in the Health Domain

Islam et al. [65] conduct a general survey on IoT for healthcare, covering a broad range of categories on the topic including networks, healthcare applications, cybersecurity, and policy. Yin et al. [66] provide an overview of IoT for healthcare, highlighting key considerations such as communication standards and protocols, sensing devices, and implementation strategies. The review by Qi et al. [67] focuses on the use of IoT in personalised healthcare systems, reviewing the sensors used, communication standards, and data processing techniques. Similarly, Philip et al. [68] survey the use of IoT in health monitoring systems, exploring advances in the field such as cloud computing, sensor devices, and communication networks. Albahri et al. [69] focus on health monitoring systems for telemedicine applications, highlighting techniques that support the connection of hospital services to remote patients.

There have also been reviews specifically focusing on the wearable sensors that are used for health monitoring. Dias and Cunha [14] survey wearable health devices, technologies, and systems, while Majumder et al. [70] present a state-of-the-art review of wearable sensors for remote health and activity monitoring. Similarly, Baig et al. [71] analyse wearable patient monitoring systems and highlight their potential for clinical adoption. Kim et al. [72] focus on advances in wearable sensors, honing in on biosensors that detect biofluids, such as sweat and tears. The review by Punj and Kumar [73] focuses on the technological aspects of body area networks for health monitoring, providing an overview of the collection, transmission, communication, and analysis of sensor data. Banaee et al. [74] survey data mining methods for wearable sensor data in health monitoring systems, while Andreu-Perez et al. [18] provide an overview of the evolution of sensor-based healthcare and advances in sensor data processing.

While these reviews provide useful analyses on the role of sensors and IoT in health monitoring, they either do not mention semantic technologies or do so briefly without an in-depth analysis of their role in health monitoring.

3.3. Group 3: Semantic Technologies for Sensors and IoT

Honti and Abonyi [75] survey the use of semantic technologies, particularly ontologies, in IoT-based systems in different domains, while Rhayem et al. [76] present a similarly domain-agnostic review of Semantic Web technologies for IoT applications, also choosing to focus on ontologies. Compton et al. [9] present a state-of-the-art review of the semantic specification of sensors using ontologies, analysing the range and expressive power of sensor ontologies. Bajaj et al. [45] adopt a similar focus on ontologies, reviewing both general sensor ontologies as well as domain-specific ones for IoT. The review by Harlamova et al. [77] explores the challenges in the use of semantic technologies in IoT, including scalability, standardisation, and data interpretation. Ye et al. [78] review the application of Semantic Web technologies in pervasive and sensor-driven systems, highlighting the benefits of these technologies and identifying open issues in the area. Although these reviews highlight the use of semantic technologies with sensors and IoT, they are not specific to the health domain.

3.4. Other reviews related to AI and Technology in the Health Domain

A small number of reviews take a broader lens and consider different aspects of AI and technology in the health domain. This includes the concept of Healthcare 4.0, a term referring to the increasing digitisation of the healthcare industry. The reviews by Tortorella et al. [79] and Jayaraman et al. [80] broadly cover Healthcare 4.0, and highlight health monitoring systems that use IoT and sensors. However, only the review by Jayaram et al. [80] mentions ontologies and other knowledge representation techniques. Behera et al. [81] review the role of cognitive computing in healthcare, focusing on techniques used to create healthcare systems modeled on the human cognitive processes such as perception and thought. In their review, they include cognitive IoT as a future research direction, highlighting the importance of wearable sensors in health monitoring, while also mentioning semantic technologies for knowledge representation. However, neither the semantic technologies nor wearable sensors are discussed in detail.

3.5. Summary

Table 1 summarises the related reviews. The current study differs from existing work by focusing on the use of sensors and semantic technologies for personal health monitoring, with both sensor data and semantic technologies being primary points of focus. Additionally, the majority of the related reviews and surveys do not take a systems perspective, whereas this study highlights how the different system components are integrated and discusses the architectures, methodologies, and evaluation approaches of the included systems.

Table 1

Summary of related reviews and their focus areas. Key: ✓ - the area is a main focus area of the review; † - the area is partially addressed, but is not discussed in depth and is not a main focus area of the review; ✗ - the area is not addressed at all in the review.

Group	Review	Year	Semantic Technologies	Healthcare/ Health Monitoring	Sensors/IoT
1. Semantic Technologies in the Health Domain	Dimitrieski et al. [63]	2016	✓	✓	✗
	Hammad et al. [62]	2020	✓	✓	†
	Haque et al. [60]	2022	✓	✓	†
	Jing et al. [64]	2023	✓	✓	✗
	Peng et al. [61]	2020	✓	✓	†
	Zenuni et al. [59]	2015	✓	✓	✗
2. Sensors and IoT in the Health Domain	Albahri et al. [69]	2018	✗	✓	✓
	Andreu-Perez et al. [18]	2015	†	✓	✓
	Baig et al. [71]	2017	✗	✓	✓
	Banaee et al. [74]	2013	†	✓	✓
	Dias and Cunha [14]	2018	✗	✓	✓
	Islam et al. [65]	2015	†	✓	✓
	Kim et al. [72]	2019	✗	✓	✓
	Majumder et al. [70]	2017	✗	✓	✓
	Philip et al. [68]	2021	†	✓	✓
	Punj and Kumar [73]	2019	✗	✓	✓
	Qi et al. [67]	2017	†	✓	✓
	Yin et al. [66]	2016	†	✓	✓
3. Semantic Technologies for Sensors and IoT	Bajaj et al. [45]	2017	✓	†	✓
	Compton et al. [9]	2009	✓	✗	✓
	Harlamova et al. [77]	2017	✓	†	✓
	Honti and Abonyi [75]	2019	✓	†	✓
	Rhayem et al. [76]	2020	✓	✗	✓
	Ye et al. [78]	2015	✓	✗	✓
Other Related Reviews	Behera et al. [81]	2019	†	✓	†
	Jayaraman et al. [80]	2020	†	✓	†
	Tortorella et al. [79]	2020	✗	✓	†
This study			✓	✓	✓

4. Methodology

4.1. Objectives and Reporting Strategy

In order to achieve our goal of mapping the state of the art in the use of semantic technologies in sensor-based personal health monitoring systems, the following are the objectives of this study:

1. To systematically select systems that represent the state of the art in the use of semantic technologies in sensor-based personal health monitoring systems.
2. To determine the research challenges addressed by the systems.
3. To determine the role that semantic technologies play in addressing these challenges.
4. To highlight inadequacies in existing systems and provide recommendations for future research.

Given the goal and objectives of this work, a mapping study was the most appropriate approach. Although systematic mapping studies are similar to systematic literature reviews in terms of the systematic process of searching for and selecting studies, literature reviews aim at synthesizing evidence while mapping studies structure a research area through classification and categorisation in order to discover research trends [82]. The study was conducted and is reported using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [83] framework. PRISMA was selected due to its establishment as a transparent and concise reporting strategy in several research fields, including computing [84]. To further ensure the quality of the study, the quality assessment criteria adapted by Kitchenham et al. [85] were adhered to as follows:

1. "The inclusion criteria are explicitly defined in the paper": This is done in Section 4.3.
2. "The authors have either searched four or more digital libraries and included additional search strategies or identified and referenced all journals addressing the topic of interest": Six digital libraries were searched, as outlined in Section 4.2. Additionally, systems included in the related reviews were also assessed for inclusion in this study.
3. "The authors have explicitly defined quality criteria and extracted them from each primary study": The systems are evaluated based on the six identified challenges, with the specific evaluation aspects outlined in Table 9.
4. "Information is presented about each paper so that the data summaries can clearly be traced to relevant papers": A summary of all the included systems is shown in Table 4, and all the systems are fully cited.

4.2. Search Strategy

Six digital libraries were searched between 5th and 7th December 2022: ACM Digital Library[17], IEEE Xplore[18], PubMed[19], ScienceDirect[20], Scopus[21], and Web of Science[22]. For all libraries, the abstracts, titles and/or keywords were searched using terms related to the topic of the study, at the intersection of five areas: semantic technologies, sensors, the health domain, monitoring, and systems. The search strings used are shown in Table 2. Boolean operators were used for a more specific search, although the ScienceDirect library had a limit on the number of Boolean operators that could be used per search. This library also did not allow the use of wildcard characters. Across all libraries, the results were filtered to only include literature published in or after 2012 to ensure a state of the art study. Additionally, where possible, the results were filtered to only include conference papers and journal articles published in English. This filtered out other types of literature such as surveys and reviews, books and book chapters, research abstracts, posters, and conference proceedings, as well literature written in languages other than English. This initial search yielded 725 results.

Table 2

Search strings used in digital library search.

Area	**Search strings**
Semantic technologies	semantic*, ontolog*, knowledge graph, linked data
Sensors	sensor*, iot, internet of things, wearable*, device*, body area network
Health domain	health*, medic*
Monitoring	monitor*, track*, remote, tele*, distributed, continuous, daily
Systems	system, framework, application, architecture

[17]https://dl.acm.org/
[18]https://ieeexplore.ieee.org/Xplore/
[19]https://pubmed.ncbi.nlm.nih.gov/
[20]https://www.sciencedirect.com/
[21]https://www.scopus.com/
[22]https://www.webofscience.com/

4.3. Inclusion and Exclusion Criteria

This study includes only peer-reviewed journal articles and conferences papers reporting original research and written in English. Therefore, other types of literature such as books, research abstracts, proposals, surveys, and reviews were excluded. Only systems that incorporate semantic techniques are included for analysis. As such, systems that do not have a well-defined semantic technique as an integral component are excluded. Additionally, because a system consists of several components that are integrated in some way, studies reporting the development of only one component (for example, an ontology) are excluded. Of particular interest are sensors that measure physiological data (that is, biosignals and vital signs), as these are significant for health monitoring. Therefore, systems that do not include such sensors are excluded from this study. Related to this, applications of sensors outside health monitoring are also excluded. Consequently, systems focusing solely on other areas such as activity recognition, sports, fitness, and nutrition are not included in this study. Finally, systems that do not have an analysis, inferencing, or reasoning component are excluded. This is because health monitoring systems must not only collect sensor data but also use the data to draw meaningful insights. These criteria are summarised in Table 3.

Table 3
Inclusion and exclusion criteria.

#	Criteria	Inclusion Criteria	Exclusion Criteria
C1	Publication Year	The year of publication is 2012 or later.	The year of publication is earlier than 2012.
C2	Language	The publication is written in English.	The publication is written in a language other than English.
C3	Publication Type	The publication is a peer-reviewed journal article or conference paper reporting original research.	The publication is either not peer-reviewed (e.g. research abstracts, posters, books, and keynotes), is a collection of works (e.g. conference proceedings), or does not report original research (e.g. reviews, surveys, and position papers).
C4	Accessibility	The publication is open access.	The publication requires payment to access.
C5	Multiple Integrated Components	The publication must report on a system, framework, application, or architecture consisting of several integrated components.	Studies reporting the development of only one component (e.g. an ontology).
C6	Semantic Technologies	The system incorporates semantic technologies as an integral component.	Semantic technologies are either poorly defined or do not form an integral component of the system.
C7	Health Monitoring	The system focuses on health monitoring.	The system has a focus outside the health domain, or is related to health but does not focus on health monitoring (e.g. systems focusing solely on other areas such as activity recognition, sports, fitness, and nutrition).
C8	Sensors for Physiological Data	The system incorporates sensors that measure physiological data (i.e. biosignals and vital signs).	The system does not incorporate sensors or the sensors incorporated do not measure physiological data.
C9	Analysis & Reasoning	The system has an analysis, inferencing, or reasoning component.	The system does not analyse or reason over the sensor data.
C10	Extended Work	If the system has been extended in future work, the more recent version is included in the review.	The system is extended in future work.

4.4. Selection Results

7 additional records were identified through screening the systems referenced in the related reviews. These were added to the 725 search results, resulting in 732 total identified records. 247 duplicate records were removed resulting in 485 unique records. Next, preliminary screening was done by reviewing the title and abstract of each record after which 365 records were excluded. The remaining 120 papers were read in full to determine if they still met the inclusion criteria. One reason for exclusion at this stage was if the system had been extended in future work and the extension was one of the systems being assessed. In such cases, the extension was included in the study

while the previous work was excluded. The result of the selection process was a total of 40 systems selected for this study. Figure 2 shows the flow diagram of the identification, screening, eligibility, and inclusion process.

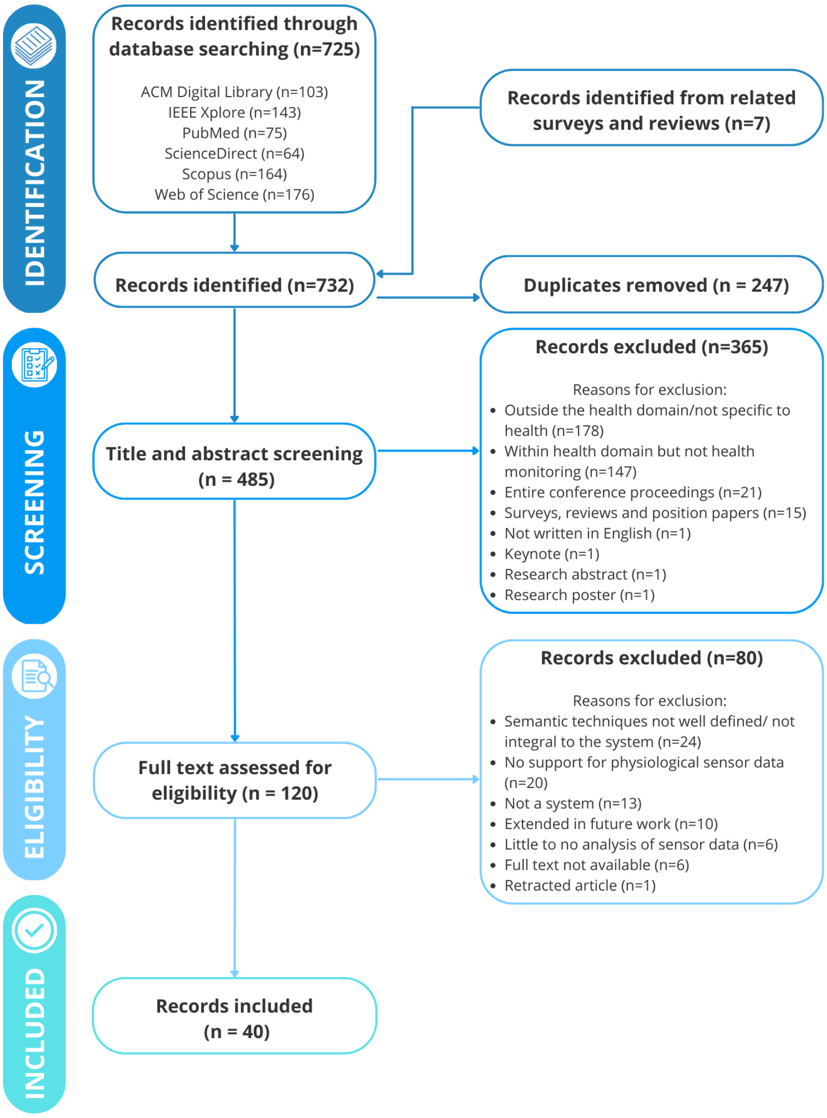

Fig. 2. PRISMA flow diagram outlining the selection process, the number of records included and excluded at each phase, and the reasons for exclusion.

4.5. Summary of systems

Table 4 summarises the 40 systems, while Figure 3 shows the distribution of the systems according to the publication year. The year of publication ranges from 2012 to 2022, with 2021 being the most common. In terms of the application area, 23 focus on a particular disease or diseases, while the remaining 17 provide a solution for general health monitoring. Regarding the types of semantic technologies used in the systems, nearly all of them make use of ontologies. The exceptions are the systems proposed by Yu et al. [86] and Zhou et al. [87] which use only knowledge graphs, and the one proposed by Xu et al. [88], which uses both linked data and a knowledge graph. Similarly, Reda et al. [89] use both linked data and an ontology, while Stavropoulos et al. [90] use both a knowledge graph and an ontology. With respect to the types of data used in the systems, all 40 systems collect physiological and other body data. 13 systems additionally incorporate environmental data from ambient sensors, while 18 consider data from existing health and medical records. Table 5 shows the types of sensor data and non-sensor data sources used by the systems. A more detailed discussion and analysis of the systems follows in the next section.

Table 4
Summary of systems selected for this study.

#	System	Year	Application	Semantic Technologies	Other Techniques	Architecture Type
1	Akhtar et al. [91]	2022	Parkinson's	Ontology	Agents; CDL; Rules	Layered; multi-agent
2	Ali et al. [92]	2021	Diabetes; ABP	Ontology	ML; NLP; Rules	Layered
3	Ali et al. [93]	2020	Heart disease	Ontology	ML; Rules	Layered
4	Ali et al. [94]	2018	Diabetes	Ontology	FL; Queries; Rules	Layered
5	Alti et al. [95]	2022	Diabetes	Ontology	Agents; Queries; Rules	Layered; multi-agent; service-oriented
6	Chatterjee et al. [96]	2021	Obesity	Ontology	Queries; Rules	Modular
7	Chiang and Liang [97]	2015	General monitoring	Ontology	FL; Rules	Modular
8	De Brouwer et al. [98]	2022	Headache disorders	Ontology	ML; Queries; Rules	Modular
9	El-Sappagh et al. [99]	2019	Diabetes	Ontology	Queries; Rules	Modular
10	Elhadj et al. [100]	2021	General monitoring	Ontology	Rules	Layered
11	Esposito et al. [101]	2018	Arrhythmia	Ontology	FL; Rules	Layered
12	Fenza et al. [102]	2012	General monitoring	Ontology	Agents; FL; Rules	Layered; multi-agent; service-oriented
13	Garcia-Valverde et al. [103]	2014	General monitoring	Ontology	ML; Rules	None mentioned
14	Hadjadj and Halimi [104]	2021	General monitoring	Ontology	Queries; Rules	Layered
15	Henaien et al. [105]	2020	General monitoring	Ontology	ML; Queries; Rules	Layered
16	Hooda and Rani [106]	2020	Diabetes; heart disease	Ontology	Queries; Rules	Modular
17	Hristoskova et al. [107]	2014	Heart failure	Ontology	Rules	Service-oriented
18	Hussain and Park [108]	2021	Stroke	Ontology	ML; Queries; Rules	Modular
19	Ivașcu and Negru [109]	2021	General monitoring	Ontology	Agents; ML; Queries; Rules	Modular; multi-agent
20	Ivașcu et al. [110]	2015	Mental illnesses; degenerative disorders	Ontology	Agents; Rules	Modular; multi-agent
21	Khozouie et al. [111]	2018	General monitoring	Ontology	Rules	Modular
22	Kim et al. [112]	2014	General monitoring	Ontology	Queries; Rules	Layered
23	Kordestani et al. [113]	2021	Kidney disease; skin disease	Ontology	ASP; Rules; BN	Layered
24	Mavropoulos et al. [114]	2021	General monitoring	Ontology	Agents; ML; NLP; Rules	Layered; modular; single-agent
25	Mcheick et al. [115]	2016	Stroke	Ontology	BN	Layered
26	Mezghani et al. [116]	2015	Diabetes	Ontology	ML; Queries; Rules	Layered; service-oriented
27	Minutolo et al. [117]	2016	Arrhythmia	Ontology	FL; Rules	Modular
28	Peral et al. [118]	2018	Diabetes	Ontology	ML; NLP; Rules	None mentioned
29	Reda et al. [89]	2022	General monitoring	Linked Data; Ontology	Queries; Rules	Layered
30	Rhayem et al. [119]	2021	Gestational diabetes	Ontology	Queries; Rules	Modular
31	Spoladore et al. [120]	2021	Diabetes; pulmonary disease	Ontology	Queries; Rules	Layered
32	Stavropoulos et al. [90]	2021	Multiple sclerosis	Knowledge graph; Ontology	Rules	Modular
33	Titi et al. [121]	2019	General monitoring	Ontology	Queries; Rules	Layered
34	Vadillo et al. [122]	2013	General monitoring	Ontology	Agents	Layered; multi-agent
35	Villarreal et al. [123]	2014	Diabetes	Ontology	None specified	Layered
36	Xu et al. [88]	2017	General monitoring	Linked data; Knowledge graph	CBR; Queries	Layered; service-oriented
37	Yu et al. [86]	2022	Paediatric asthma	Knowledge graph	ML; NLP; Rules	Modular
38	Yu et al. [124]	2017	General monitoring	Ontology	Queries; Rules	Layered
39	Zhang et al. [125]	2014	General monitoring	Ontology	Rules	Layered; modular
40	Zhou et al. [87]	2022	General monitoring	Knowledge graph	ML	Modular

ABP - Abnormal blood pressure; ASP - Answer set programming; BN - Bayesian network; CBR - Case-based reasoning; CDL - Contextual defeasible logic; FL - Fuzzy logic; ML - Machine learning; NLP - Natural language processing.

Table 5
Types of sensor data and other sources of data used by the systems.

#	System	Supported Sensor Data and Other Data Sources
1	Akhtar et al. [91]	**Body** (BP, HR, BT, ECG, EEG, EMG); **Ambient** (temperature, CO & CO_2 levels, motion)
2	Ali et al. [92]	**Body** (BP, SpO_2, BT, HR, ECG, EEG, BG); **Other** (health/medical records, social networks, smartphone)
3	Ali et al. [93]	**Body** (RR, SpO_2, BP, BT, HR, EMG, EEG, ECG, BG, cholesterol, position, activity); **Other** (health/medical records)
4	Ali et al. [94]	**Body** (ECG, EEG, EMG, HR, BP, BG, cholesterol, range of motion)
5	Alti et al. [95]	**Body** (HR, BG, motion, global positioning system)
6	Chatterjee et al. [96]	**Body** (BP, BG, activity); **Ambient** (temperature, humidity); **Other** (interviews, questionnaires, weather forecast, health/medical records)
7	Chiang and Liang [97]	**Body** (BP, HR, BG, cholesterol); **Ambient** (motion, indoor & outdoor temperature, humidity)
8	De Brouwer et al. [98]	**Body** (Accelerometer, other unnamed physiological data); **Other** (self-reported data)
9	El-Sappagh et al. [99]	**Body** (BP, HR, BG); **Other** (health/medical records)
10	Elhadj et al. [100]	**Body** (BT, HR, BP, RR, SpO_2); **Ambient** (temperature, humidity, location); **Other** (health/medical records)
11	Esposito et al. [101]	**Body** (BT, HR, SpO_2, accelerometer)
12	Fenza et al. [102]	**Body** (HR, BP, BT, SpO_2, BG); **Ambient** (temperature)
13	Garcia-Valverde et al. [103]	**Body** (HR, accelerometer, gyroscope, magnetoresistance)
14	Hadjadj and Halimi [104]	**Body** (BP, HR, BT, BG); **Other** (vehicle sensor data)
15	Henaien et al. [105]	**Body** (SpO_2, BP, HR, RR, BT); **Ambient** (temperature, light, motion); **Other** (health/medical records)
16	Hooda and Rani [106]	**Body** (BP, HR, BG, ECG); **Other** (health/medical records)
17	Hristoskova et al. [107]	**Body** (BP, HR, SpO_2, ECG); **Other** (health/medical records)
18	Hussain and Park [108]	**Body** (ECG); **Other** (health/medical records)
19	Ivașcu and Negru [109]	**Body** (HR, RR, ECG, accelerometer)
20	Ivașcu et al. [110]	**Body** (EEG, accelerometer); **Ambient** (video, audio, motion, bed sensor data)
21	Khozouie et al. [111]	**Body** (BP, BT, SpO_2, ECG, EMG, accelerometer, gyroscope); **Ambient** (temperature, humidity, CO & O_2 levels)
22	Kim et al. [112]	**Body** (BP; other unnamed vital signs); **Ambient** (temperature, illumination, humidity, wind); **Other** (weather forecast, news, weather indices)
23	Kordestani et al. [113]	**Body** (BT, other unnamed vital signs); **Ambient** (temperature); **Other** (health/medical records)
24	Mavropoulos et al. [114]	**Body** (BP, BG, sleep); **Ambient** (video); **Other** (health/medical records)
25	Mcheick et al. [115]	**Body** (BP, blood flow velocity)
26	Mezghani et al. [116]	**Body** (BP, HR, BG); **Other** (health/medical records)
27	Minutolo et al. [117]	**Body** (BT, HR, SpO_2m accelerometer)
28	Peral et al. [118]	**Body** (BG); **Other** (the web, existing databases, health/medical records)
29	Reda et al. [89]	**Body** (HR, BT, BP, weight, calories burned, step count); **Other** (self-reported data)
30	Rhayem et al. [119]	**Body** (BT, BP, HR, BG, cholesterol, activity); **Ambient** (temperature, humidity); **Other** (health/medical records)
31	Spoladore et al. [120]	**Body** (HR, SpO_2)
32	Stavropoulos et al. [90]	**Body** (HR, step count, sleep)
33	Titi et al. [121]	**Body** (BT, BP, HR, BG); **Ambient** (temperature, humidity)
34	Vadillo et al. [122]	**Body** (HR, BT, BP, SpO_2, BG); **Ambient** (motion, temperature, bed/chair occupancy, CO levels)
35	Villarreal et al. [123]	**Body** (BP, BT, BG)
36	Xu et al. [88]	**Body** (BP, ECG, BG); **Other** (health/medical records)
37	Yu et al. [86]	**Body** (BP, HR, sleep, exercise, weight); **Other** (health/medical records, self-reported data)
38	Yu et al. [124]	**Body** (HR, BP, body fat); **Other** (mobile applications)
39	Zhang et al. [125]	**Body** (BP, BT, HR, SpO_2); **Other** (health/medical records)
40	Zhou et al. [87]	**Body** (BP, HR, RR, BT, SpO_2, BG, uric acid, cholestrol, lipoproteins, triglycerides, sleep); **Ambient** (inhalable particulate matter, CO_2, temperature, formaldehyde, total volatile organic compounds); **Other** (health/medical records)

BG - blood glucose; BP - blood pressure; BT - body temperature; CO_2 - carbon dioxide; CO - carbon monoxide; ECG - electrocardiogram; EEG - electroencephalogram; EMG - electromyogram; HR - heart rate; O_2 - oxygen; RR - respiratory rate; SpO_2 - blood oxygen saturation

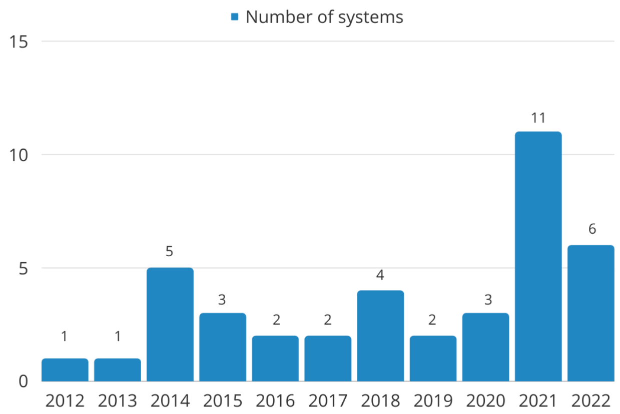

Fig. 3. Bar graph showing the distribution of the systems by year of publication.

5. Key Challenges in Health Monitoring Systems

Based on an understanding of the issues of using sensor data and the essential functionalities necessary for reliable health monitoring, there are several factors that must be taken into consideration when developing personal health monitoring systems. These can be distilled into six key challenges: interoperability, context awareness, situation detection, situation prediction, decision support, and uncertainty handling. This section provides an overview of these challenges and a detailed analysis of how they are achieved in the systems. The role of semantic technologies in addressing each challenge is discussed, as well as other technologies and techniques that are incorporated in the systems. The section concludes by critically evaluating the extent to which each system addresses these challenges.

5.1. Interoperability

Interoperability can be defined as the ability of different components or systems to not only exchange information but also to make use of it [126]. There are three types of interoperability identified in the health domain: technical, semantic, and process interoperability [126, 127]. Technical interoperability pertains to the way data or information moves from one system or component to another. Related to this is syntactic interoperability, which provides a structure and syntax for the transmitted data [128]. Semantic interoperability refers to the ability of the recipient to understand and make use of the received data, whereas process interoperability concerns the way in which different systems are used in actual work settings. A subset of this is clinical interoperability, through which patients can seamlessly be transferred between different care teams [126].

5.1.1. Technical Interoperability

Differing data transmission technologies can contribute to a lack of technical interoperability in health monitoring systems, particularly those that use a range of different sensors. Data transmission protocols used in sensors include Bluetooth, Bluetooth Low Energy, ANT+, and Zigbee, with the first three being the most common among wearable devices today [13]. Interoperability among these different protocols can be achieved using gateway devices, which receive data from different sensors and transmit it to cloud services [129]. This is done by Ali et al. [94], who use a router as a gateway to receive sensor data and transmit it to the internet. A number of the systems [93, 95, 99, 100, 108, 111, 118, 123, 125] use a mobile phone as a gateway device or base station, typically receiving sensor data via Bluetooth or Bluetooth Low Energy and transmitting it to the cloud via Wi-Fi or mobile data.

5.1.2. Syntactic Interoperability

While technical interoperability is associated with hardware components and infrastructure, syntactic interoperability is usually associated with data formats [130]. There are several standards that are widely used to promote syntactic interoperability among systems. Among them is the ISO/IEEE 11073 standard, which provides a common format for communication involving medical devices and patient health data, with an emphasis on vital signs. This standard is used by El-Sappagh et al. [99] for message formatting between body sensors and the base unit. Other important standards for health data are provided by Health Level 7 (HL7). One of these is Fast Health Interoperability Resources (FHIR), which describes data formats, resources, and an application programming interface (API) through which health information can be exchanged [126]. El-Sappagh et al. [99] integrate FHIR in their proposed system, converting sensor data from the ISO/IEEE 11073 standard to FHIR resource formats. Additionally, the system receives data in FHIR format from hospital information systems. In this way, both sensor data and data from hospital systems are in the same format. FHIR resources can be defined using different data formats[23], including Extensible Markup Language (XML), JavaScript Object Notation (JSON), and Terse RDF Triple Language (Turtle).

5.1.3. Semantic Interoperability

The next type of interoperability is semantic interoperability, which is concerned with the meaning of the exchanged information. Semantic interoperability can be achieved through the use of unambiguous codes and identifiers, which can be provided by existing standard classifications and terminologies [126, 131]. Ontologies are, of course, a well-established way to embed semantic interoperability in a system [32], and many existing medical terminologies are available as ontologies. Among the systems, SNOMED CT is the most commonly used medical terminology [87, 89, 96, 99, 113, 119, 121]. Others are ICNP, which is used by Elhadj et al. [100] and Henaien et al. [105], and ICD, which is used by Spoladore et al. [120] and Titi et al. [121]. The Unified Medical Language System (UMLS) [132] is a large thesaurus integrating multiple medical knowledge terminologies, including SNOMED CT and ICD. It is used by Peral et al. [118] and Zhou et al. [87]. Another thesaurus is Medical Subject Headings (MeSH), which is used for indexing, cataloging, and searching health information, and is integrated in the system proposed by Reda et al. [89]

Terminologies for specific diseases and conditions also exist. For example, De Brouwer et al. [98] use the International Classification of Headache Disorders (ICHD)[24], while Spoladore et al. [120] used the International Classification of Functioning, Disability and Health (ICF)[25]. The Vital Sign Ontology is extended by El-Sappagh [99] and Ivașcu and Negru [109], while some authors, such as Ali et al. [92], El-Sappagh et al. [99], and Hristoskova et al. [107], opt to use existing ontologies focused on their specific health applications, i.e. diabetes and heart failure respectively. Xu et al. [88] posit that it is difficult to build scalable ontology-based systems suitable for large amounts of healthcare data, and instead opt for a linked data approach to add semantic information to the data. Their proposed system uses linked open data medical knowledge bases, namely Diseasome, DBpedia, and DrugBank. Using these knowledge bases, they create a knowledge graph showing the relations between symptoms and diseases.

Semantic technologies also provide a means to represent sensors and the data they capture. Sensors can be represented with varying degrees of expressiveness. Concepts that can be captured about sensors include unique identifier, manufacturer, location of deployment, dimensions, operating conditions, type of data captured, and hierarchy with regards to related sensors [9]. Similarly, various sensor data concepts can be represented, such as the property being observed, units of measurement, and measurement timestamps. A majority of the systems represent sensor and sensor data concepts in ontologies, with 10 re-using and extending existing sensor or device ontologies, namely SSN/SOSA [90, 96, 99, 100, 109, 119, 121], SAREF and its extensions [98, 104], the Amigo device ontology [107], and the Moving Objects ontology [119]. Table 6 shows the systems that re-use existing ontologies, knowledge bases, terminologies, and standards. Generally, the systems that re-use existing ontologies have a higher degree of expressiveness for sensor and sensor data concepts than those that do not. This facilitates more effective querying of and reasoning on sensor data, which is essential for situation analysis. Comprehensive

[23] https://build.fhir.org/resource-formats.html
[24] https://ichd-3.org/
[25] https://icd.who.int/dev11/l-icf/en

sensor ontologies also support sensor management, allowing sensors to be catalogued based on their attributes as captured in ontologies.

Table 6

Re-used ontologies, knowledge bases, terminologies, and standards.

#	System	Re-used Ontologies, Terminologies & Standards
1	Ali et al. [92]	Ontology for Nutritional Studies; BioMedBridges Diabetes Ontology; Diabetes Mellitus Treatment Ontology; Human Disease Ontology; Drug Target Ontology; FHIR And SSN-based Type 1 Diabetes Ontology
2	Chatterjee et al. [96]	SSN Ontology; SNOMED CT
3	El-Sappagh et al. [99]	Basic Formal Ontology; SSN Ontology; SmartBAN Ontology; SNOMED CT; Vital Sign Ontology; Diabetes Mellitus Diagnosis Ontology; SWRL Temporal Ontology; ISO/IEEE 11073; FHIR
4	De Brouwer et al. [98]	SAREF Ontology; SAREF4ehaw Ontology; ICHD-3
5	Elhadj et al. [100]	SSN/SOSA Ontology; FOAF Ontology; ICNP
6	Fenza et al. [102]	OWL-S
7	Hadjadj and Halimi [104]	SAREF4Wear Ontology
8	Henaien et al. [105]	SSN/SOSA Ontology; FOAF Ontology; ICNP
9	Hristoskova et al. [107]	Amigo device ontology; Heart failure ontology; OWL-S
10	Ivașcu and Negru [109]	Vital Sign Ontology; Physical Activity Concept Ontology; SSN Ontology; MIMU-Wear Ontology; HealthIoT Ontology
11	Kordestani et al. [113]	SNOMED CT
12	Mavropoulos et al. [114]	OWL-Time Ontology; FOAF Ontology; General User Model Ontology; COPDology; OwlSpeak Ontology
13	Peral et al. [118]	UMLS; WordNet; Cyc Ontology
14	Reda et al. [89]	SNOMED CT; FOAF; Basic Geo (WGS84 lat/long) Vocabulary; DBpedia; MeSH; WordNet
15	Rhayem et al. [119]	SNOMED CT; SSN Ontology; OWL-Time Ontology; IoT-lite Ontology; GeoNames Ontology; Moving Object Ontology
16	Spoladore et al. [120]	ICD-11; ICF; Food Ontology
17	Stavropoulos et al. [90]	SOSA Ontology; DOLCE+DnS Ultralite Ontology; Web Annotation Data Model
18	Titi et al. [121]	SNOMED CT; ICD-10; SSN/SOSA Ontology; FOAF Ontology; OWL-Time Ontology
19	Xu et al. [88]	Diseasome; DBpedia; DrugBank
20	Yu et al. [86]	ICD-10
21	Yu et al. [124]	Translational Medicine Ontology; Medical Web Lifestyle Aggregator; FOAF Ontology; OWL-Time Ontology; Informed Consent Ontology; Annotation Ontology; Places Ontology; Event Ontology
22	Zhou et al. [87]	UMLS; SNOMED CT

FHIR - Fast Healthcare Interoperability Resources; FOAF - Friend of a Friend; ICD - International Classification of Diseases; ICHD - International Classification of Headache Disorders; ICNP - International Classification for Nursing Practice; MeSH - Medical Subject Headings; MIMU - Magnetic and Inertial Measurement Units; SAREF4ehaw - SAREF for eHealth and ageing well; SAREF4wear - SAREF for wearables; SAREF - Smart Applications REFerence; SNOMED CT - Systematized Nomenclature of Medicine Clinical Terms; SOSA - Sensor, Observation, Sample, and Actuator; SSN - Semantic Sensor Network; UMLS - Unified Medical Language System

5.1.4. Process Interoperability

The final type of interoperability is process interoperability, which focuses on how systems and components work seamlessly together in real-world settings. One way to enhance process interoperability in health monitoring systems is through the integration of sensor data with comprehensive health and medical records [127]. The inclusion of these records allows health monitoring systems to complement and extend healthcare provided in clinical settings. Health and medical records provide additional information that is useful for health monitoring, such as an individual's disease history, laboratory test results, medications taken, allergies, and previous hospital admissions. About half of the systems integrate existing records in some way, with most of them represented using ontologies. The systems proposed by Ali et al. [93, 94], El-Sappagh [99], and Rhayem et al. [119] have the most comprehensive records, capturing laboratory tests, prior disease diagnoses, and lifestyle information such as exercise, nutrition, alcohol consumption, and smoking status. Some systems use medical records to extract diagnosis status [92], while others use them to extract an individual's risk factors for disease [93]. These records can also be used to overcome limitations of sensor data such as missing values, as was done by Ali et al. [92]. Besides health and medical records, data from social networks and other web and mobile applications can also be used to complement sensor data. For instance, Ali et al. [92] use social networking data for monitor individuals' mental health through sentiment analysis.

5.2. Context Awareness

Health monitoring systems must be able to adapt based on the context of the individual being monitored. The four most common aspects of context are location, time, identity (of a person or agent), and activity (or events) [43, 44].

5.2.1. Location

Ye et al. [44] highlight three types of locations that can be represented: symbolic locations, coordinate locations, and regions. The systems proposed by Akhtar et al. [91], Chiang and Liang [97], and Vadillo et al. [122] keep track of the different rooms in a house where an individual may be, while those proposed by Khozouie et al. [111] and Titi et al. [121] indicate more generally the place the monitored individual is (for example, "home" or "hospital"). These are symbolic locations. One purpose of such locations is to allow the systems to suggest relevant services based on the type of space currently occupied, as is the case in the system proposed by Chiang and Liang [97]. In the system proposed by Hristoskova et al. [107], the physician's location (i.e. the room they occupy in a hospital) is used to determine which device to send notifications to, optimising for the closest device. This is similar to the system proposed by Alti et al. [95], which supports a GPS sensor that captures the current coordinates of the monitored individual. In this system, location is used to select devices closest to the user from which to deploy health services so as to increase efficiency and minimise inter-device communication costs. Coordinate locations also serve the purpose of alerting caregivers and emergency services of the exact location of a person in the event of a medical emergency, as is suggested by Rhayem et al. [119]. The system proposed by Hadjadj and Halimi (2021) [104] integrates health monitoring in the public transport system, and therefore includes location sensors in public transportation vehicles. The final type of location is regions, which are geometrical two- or three-dimensional representations of locations [44]. This type of location is used in the system proposed by Kim et al. [112] in order to advise users of region-specific situations, such as adverse or dangerous weather. Similarly, El-Sappagh et al. [99] use the spatial region class from the Basic Formal Ontology to represent the patient's current location, as well as the placement of the sensors. Despite the importance of location as an aspect of context, less than half of the systems include it.

5.2.2. Time

In contrast, nearly all of the systems include the concept of time. Observation time is the most common way time is incorporated in the systems, with many systems capturing the exact timestamp for each sensor observation [90, 95, 96, 98–101, 104, 108, 110, 114, 117, 119, 121, 122]. Besides observation time, the time at which certain events occur can be captured, for example calls to emergency services [95]. This allows the systems to display or analyse trends over time. Additionally, Alti et al. [95] capture the time intervals in which reports should be sent. Rather than a timestamp, several systems also capture the general time of day during which observations or activities occur. For instance, Ali et al. [92] divide the time at which daily activities are done into morning, afternoon, and evening. Peral et al. [118] use mealtimes as a point of reference, which is particularly important when taking blood glucose measurements. They distinguish between pre-breakfast, pre-lunch and pre-dinner readings.

Duration is another important aspect of time. This can be captured for physical activity [96, 120], sleep [87, 90, 96], symptoms [115], and treatment [88, 121]. De Brouwer et al. [98] capture the duration of events that can trigger headaches, such as stress. Symptom duration can influence the risk for certain illnesses, while specifying treatment duration ensures medication reminders are sent only during the prescribed period. When combined with thresholds, duration can be useful in identifying different situations. For example, Stavropoulos et al. [90] determine that an individual has a lack of movement if they have fewer than 500 steps and their heart rate has been less than 100 beats per minute for longer than 800 minutes. Related to duration is frequency. This is used by Chiang and Liang [97], Spoladore et al. [120], and Yu et al. [124] as a metric for physical activity. Mezghani et al. [116] capture the frequency of sensor observations, while Villareal et al. [123] capture the frequency of detected diseases.

Notably, valuable features can be extracted from changes in time series sensor data. For instance, Hussain and Park [108] and Ivașcu and Negru [109] use the time-domain features of the ECG to calculate heart rate and heart rate variability. Additionally, the multi-agent system proposed by Akhtar et al. [91] incorporates temporal logic, which allows for the formalization of temporal ordering operators such as "next", "always", "until", and "while" without referencing actual times [133]. Another interesting time-related aspect is trajectory, which combines both spatial and temporal properties to represent the mobility of a sensor. This is incorporated in the system proposed by Rhayem et al. [119] to define a source and destination of a sensor within a particular duration of time.

5.2.3. *Identity*

Identity, which pertains to the actors in a system, is another important aspect of context [44]. This includes the definition of individuals and their properties, such as name, address, gender, and age. For health monitoring, this can include additional information such as weight, height, and blood group. This is the most ubiquitous aspect of context in the systems, with nearly every system including personal information about the monitored individuals. Besides personal properties, identity also encompasses different user roles within the system. Most of the systems [86, 90–96, 98–101, 104, 106–110, 113–115, 118–121, 123] support different users besides the individual being monitored, typically including health professions such as nurses and physicians, and in some cases, caregivers, and family members. Identity also includes agents, which are used in the agent-based systems [91, 95, 109, 110, 114, 122]. Agents[26] have been applied extensively in the health domain [135] as well as in sensor-based systems [136]. The agent-based approach offers several advantages. For example, agents can be used as personal assistants to support humans in performing tasks and services [137]. This is explored in the system proposed by Mavropoulos et al. [114], which includes a smart virtual agent that doctors can interact with via voice commands. Agent-based architectures and their advantages are discussed in greater detail in Section 6.

5.2.4. *Activity*

The fourth essential aspect of context is activity. This can refer to physical activity or the different activities of daily living such as eating and sleeping, both of which are important considerations for situation analysis. Activity can be derived from sensors such as accelerometers, or can be deduced from location or time (for example, a person in a bedroom in the middle of the night can be assumed to be sleeping). Physical activity is closely tied to health, and there are many physical activity guidelines issued by governments and global health organisations, including the World Health Organisation [138]. Due to this link between physical activity and health, several of the systems include physical activity as contextual information. Several of the systems monitor physical activity using smartphones, smart watches, and inertial measurement units, which combine accelerometers, gyroscopes, and in some cases, magnetometers [92, 93, 98, 99, 101, 103, 109–111, 114, 117]. Chiang and Liang [97] monitor body movement using motion sensors placed around the home. This serves two purposes. Firstly, the individual's movement within the home is able to be monitored. This can determine their location at any given time. Secondly, they are able to interact with the system using body movements, such as hand-waving to activate the system. Ali et al. [94] similarly use motion sensors to keep track of body movement. They use range of motion as a metric, which is particularly important for elderly patients who may lose their ability to perform daily activities as their range of motion decreases.

Self-reported information can also be used to determine physical activity, but this may not be accurate. To mitigate this, Chatterjee et al. [96] use a combination of sensor and questionnaire data. Sensors are used to monitor number of steps and duration of activity, while questionnaires are used to determine the type of activity, for example running or weightlifting. Beyond tracking physical activity, activity recognition is also important in health monitoring. It can help in the detection of adverse events like falls, as is done in the systems proposed by Chiang and Liang [97] and Vadillo et al. [122]. Additionally, the systems proposed by Garcia-Valverde et al. [103], Ivașcu and Negru [109], Mavropoulos et al. [114], and Rhayem et al. [119] are able to recognise daily activities such as sitting, walking, and sleeping.

[26] An agent is a computer system situated in some environment that is capable of acting autonomously in order to achieve some goal(s) [134]

5.2.5. Other Types

Besides location, time, identity, and activity, other types of contextual information are incorporated in the systems. Alti et al. [95] include hardware and network information as part of context, such as available communication protocols, CPU speed, battery power, and memory size. This information is used to ensure the efficient deployment of health services. Hristoskova et al. [107] incorporate media devices and their properties in their interpretation of context. For example, the screen size of devices such as mobile phones and tablets is used to determine how to display the health monitoring results. For small screens, the results are summarised. An important factor in health monitoring is the state of a person's environment. A number of the systems use environmental data such as temperature and humidity from ambient sensors to provide additional context [87, 91, 97, 100, 102, 111–113, 119, 121, 122]. Weather data sources such as forecasts and indices are used by Kim et al. [112] to supplement sensor data, while the systems proposed by Akhtar et al. [91], Khozouie et al. [111], Vadillo et al. [122], and Zhou et al. [87] include sensors to monitor air quality by checking the levels of gases such as carbon monoxide, carbon dioxide, and oxygen. Contextual information can also include details about an individual's diet, medication, and emotional state. These details are collected in the system proposed by De Brouwer et al. [98] through self-reporting via a mobile app.

Contextual information can be represented using semantic technologies, and most of the systems do so. Among the systems that do not, the semantic technologies are typically used solely for the representation of expert health knowledge. Table 7 summarises the contextual information included in the systems and indicates which type of contextual information is captured using semantic technologies.

5.3. Situation Detection

Personal health monitoring systems should be capable of both situation detection, which is discussed in this subsection, and situation prediction, which is discussed in Section 5.4. It should be noted that context awareness is a significant contributor to effective situation analysis, since contextual information enhances sensor data and supports its interpretation.

In health monitoring systems, situation detection can take a variety of forms. One of these is the categorisation of individual sensor observations based on whether they are within or outside a given range as determined by domain knowledge. For example, in the system proposed by Akhtar et al. [91], when vital signs such as temperature and heart rate are outside the normal range, the situation is classified as an emergency. Likewise, Elhadj et al. [100] classify expected observations as normal, while observations outside the normal ranges are classified as abnormal. They also include a third classification, wrong, for faulty observations from malfunctioning sensors. Similar threshold-based situation categories are used in many of the systems [95, 98, 103, 104, 107, 109, 111, 118, 119, 121, 123, 125]. Thresholds have also been used to classify physical activity based on level of intensity [96, 99, 101, 103, 109]. A better approach than using individual sensor observations is to consider different observations and personal attributes to classify individuals. This is done by Ali et al. [94], who classify the patient health condition as either healthy, moderate, or serious based on multiple sensor outputs and properties such as sex, weight, and height. Similarly, Chiang and Liang [97] classify situations as either healthy, moderate, or severe based on age, blood pressure, blood glucose, heart rate, and cholesterol.

Another form of situation detection in health monitoring is the detection of medical conditions and diseases. Some conditions such as hypertension and hyperglycemia can be diagnosed based on individual sensor observation thresholds. This is done by Kim et al. [112], who detect prehypertension and step 1 and 2 hypertension based on defined blood pressure thresholds. Similarly, hyperglycemia is detected by Rhayem et al. [119] based on blood glucose levels. Other diseases require the analysis of signs and symptoms based on a combination of different sensor observations and other sources of data. For example, Ivașcu et al. [110] detect mental disorders (Parkinson's, Alzheimer's, psychosis, and depression) using signs and symptoms related to behaviour, motor skills, cognitive skills, facial appearance, mood, sleep, weight, and speech. Other systems are able to detect headaches [98], heart disease [93], diabetes [92, 94, 106], stroke [108], and skin and kidney diseases [113].

With regards to techniques for situation detection, 35 of the 40 systems implement some form of rule-based reasoning. Rules provide a way to implement expert knowledge in an if-then form, whereby if certain conditions are met, then a consequent conclusion is made or action taken. Despite their widespread use, rules have several

Table 7
Summary of contextual information captured in the systems and which is represented using semantic technologies (RUST).

#	System	Types of contextual information	RUST
1	Akhtar et al. [91]	**L** (patient); **T** (temporal logic); **I** (profile, user roles); **O** (air quality, weather)	**L**; **I**; **O**
2	Ali et al. [92]	**T** (activity); **I** (profile, user roles); **A** (step count, intensity level)	None
3	Ali et al. [93]	**I** (profile, user roles); **A** (intensity level)	**I**; **A**
4	Ali et al. [94]	**I** (profile, user roles); **A** (range of motion, intensity level)	**I**; **A**
5	Alti et al. [95]	**L** (patient, device); **T** (observation timestamps; report intervals); **I** (profile, user roles); **O** (hardware info, network info)	**L**; **T**; **I**; **O**
6	Chatterjee et al. [96]	**T** (observation timestamps, activity duration, sleep duration); **I** (profile, user roles); **A** (step count, intensity level, exercise type); **O** (weather)	**T**; **I**; **A**; **O**
7	Chiang and Liang [97]	**L** (patient); **T** (activity, exercise frequency); **I** (profile); **A** (detection, motion); **O** (weather, illumination)	**L**; **T**; **I**; **A**; **O**
8	De Brouwer et al. [98]	**T** (observation timestamps, trigger duration); **I** (user roles); **A** (sleep, physical activity); **O** (diet, medication, mood)	**T**; **I**; **A**; **O**
9	El-Sappagh et al. [99]	**L** (patient, sensor); **T** (observation timestamps); **I** (profile, user roles); **A** (intensity level)	**L**; **T**; **I**; **A**
10	Elhadj et al. [100]	**L** (patient); **T** (observation timestamps); **I** (profile, user roles); **O** (weather)	**L**; **T**; **A**; **O**
11	Esposito et al. [101]	**T** (observation timestamps); **I** (profile, user roles); **A** (step count, intensity level)	**T**; **I**; **A**
12	Fenza et al. [102]	**I** (profile); **O** (weather)	None
13	Garcia-Valverde et al. [103]	**T** (situation timestamps); **I** (profile); **A** (recognition, intensity level)	**T**; **I**; **A**
14	Hadjadj and Halimi [104]	**L** (vehicles, bus stop); **T** (observation timestamps); **I** (profile, user roles); **O** (passenger count, vehicle status)	**L**; **T**; **I**; **O**
15	Henaien et al. [105]	**L** (patient); **I** (profile); **A** (motion); **O** (weather)	**L**; **I**; **A**
16	Hooda and Rani [106]	**I** (profile, user roles)	**I**
17	Hristoskova et al. [107]	**L** (physician, device); **T** (risk horizon); **I** (profile, user roles); **O** (device size)	**L**; **I**; **A**; **O**
18	Hussain and Park [108]	**T** (observation timestamps; time-domain features); **I** (profile, user roles)	None
19	Ivașcu and Negru [109]	**T** (time-domain features); **I** (profile, user roles); **A** (recognition, intensity level)	**T**; **I**; **A**
20	Ivașcu et al. [110]	**T** (observation timestamps); **I** (profile, user roles); **A** (sleep quality, gait analysis)	**A**
21	Khozouie et al. [111]	**L** (patient); **T** (observation timestamps & intervals); **I** (profile); **A** (type); **O** (air quality, weather)	**L**; **T**; **I**; **A**; **O**
22	Kim et al. [112]	**L** (patient's region); **I** (profile); **O** (weather)	**L**; **A**; **O**
23	Kordestani et al. [113]	**T** (episode timestamps); **I** (profile, user roles); **O** (weather)	**I**; **O**
24	Mavropoulos et al. [114]	**T** (observation timestamps; time-domain features); **I** (profile, user roles); **A** (recognition)	**T**; **I**; **A**
25	Mcheick et al. [115]	**T** (symptom duration); **I** (profile, user roles)	**I**
26	Mezghani et al. [116]	**T** (observation start/end date, observation frequency, anomaly timestamps); **I** (profile, user roles)	**T**; **I**
27	Minutolo et al. [117]	**T** (observation timestamps); **I** (profile); **A** (step count)	**T**; **I**; **A**
28	Peral et al. [118]	**T** (observation timestamps); **I** (profile, user roles)	**T**; **I**
29	Reda et al. [89]	**L** (patient); **T** (observation timeframe); **I** (profile, user roles); **A** (step count, type, intensity)	**L**; **T**; **I**; **A**
30	Rhayem et al. [119]	**L** (patient, device trajectory); **T** (observation timestamps); **I** (profile, user roles); **A** (recognition); **O** (weather)	**L**; **T**; **I**; **A**; **O**
31	Spoladore et al. [120]	**T** (exercise timestamps, duration & frequency); **I** (profile, user roles); **A** (exercise type)	**T**; **I**; **A**
32	Stavropoulos et al. [90]	**T** (observation timestamps, sleep duration, time taken to fall asleep); **I** (profile, user roles); **A** (sleep quality, step count, intensity level)	**T**; **A**
33	Titi et al. [121]	**L** (patient); **T** (observation timestamps, intervals, & duration); **I** (profile, user roles); **A** (type, intensity level); **O** (weather)	**L**; **T**; **I**; **A**; **O**
34	Vadillo et al. [122]	**L** (patient); **T** (observation timestamps); **I** (profile); **A** (detection); **O** (air quality, weather)	**L**; **I**
35	Villarreal et al. [123]	**T** (disease duration & frequency); **I** (profile, user roles); **A** (type)	**T**; **I**; **A**
36	Xu et al. [88]	**T** (treatment duration); **I** (profile, user roles)	**I**
37	Yu et al. [86]	**I** (profile, user roles); **A** (exercise); **O** (diet, medication)	**I**; **A**; **O**
38	Yu et al. [124]	**L** (patient); **T** (disease progression, medical event timestamp; exercise frequency); **I** (profile); **A** (type)	**L**; **T**; **I**; **A**
39	Zhang et al. [125]	**T** (observation timestamps); **I** (profile)	**I**
40	Zhou et al. [87]	**T** (movement timestamps, sleep duration); **I** (profile, user roles); **A** (sleep quality); **O** (air quality, weather)	None

L - location; **T** - time; **I** - identity; **A** - activity; **O** - other

limitations. Firstly, crisp rules are unable to handle uncertainty and ambiguity in sensor observations and the determination of health situations. To mitigate this, several systems incorporate fuzzy logic [94, 97, 101, 102, 117] and defeasible logic [91] in the rules. These techniques are discussed in greater detail in Section 5.6, which focuses on techniques for handling uncertainty in health monitoring. Secondly, the manual creation of rules is time-consuming, difficult to scale, and is often static and based on existing knowledge. This challenge can be overcome using learned rules, for example based on machine learning algorithms. The systems proposed by Hussain et al. [108], Henaien et al. [105] and Peral et al. [118] extract rules from decision trees. As an alternative to rule-based reasoning, Xu et al. [88] implement case-based reasoning, arguing that it is easier to capture human experiences using cases rather than rules. By searching for historical cases that are similar to the current case, their proposed system is able to obtain treatment plans that have been successful in the past.

In addition to the development of rules as discussed above, machine learning is also used in a number of the systems for the classification of diseases based not only on sensor data but also other data sources. Ali et al. [92] use a bidirectional long short-term memory (Bi-LSTM) model to detect diabetes and blood pressure, to classify sentiments from social networking data for mental health monitoring, and to classify drug side effects. Their proposed system uses domain ontologies to extract important features that can enhance the machine learning classification. Other machine learning algorithms used include multi-layer perceptron for heart disease detection [93] and random forest for stroke detection [108]. Machine learning is also used for physical activity classification, for example using the k-nearest neighbours [103, 114], decision trees [114], and random forest [109, 114] algorithms. A full review of machine learning techniques for situation analysis in the health domain is outside the scope of this study. Readers are referred to the reviews by Ravì et al. [139] and Li et al. [140].

5.4. Situation Prediction

The determination of health risks is important in health monitoring and can be used to predict future adverse health situations. Similarly to situation detection, rules can also be used for situation prediction, with several systems taking this approach. For example, Alti et al. [95] use rules to determine the risk of death for diabetes patients based on high glucose levels and high heart rate. Rules are also used by Chiang and Liang [97] to determine the risk of arthritis recurring based on low temperatures and high humidity, and by Hristoskova et al. [107] also use rules to determine the risk of congestive heart failure (CHF) over a four-year time horizon. CHF risk stages are determined based on factors such as age, blood pressure, heart rate, and history of heart disease and diabetes. Similarly, in their use case of gestational diabetes, Rhayem et al. [119] use rules to determine the risk level for fetal loss based on age, presence of hyperglycemia, and presence of hypertension. De Brouwer et al. [98] use rule mining services to learn the association between headaches and triggers, thereby allowing the system to anticipate headache attacks.

To support the identification of potential risks, future physiological readings can also be predicted using historic sensor observations, as was done by Peral et al. [118]. Their proposed system uses machine learning algorithms (support vector machine and logistic regression) to predict blood glucose levels over three-day and five-day windows. These predictions of sensor measurements can then be analysed to determine future health risks. Besides rules and machine learning, another technique used in some of the systems is Bayesian networks. Mchiek et al. [115] use a Bayesian network to calculate the risk of stroke occurring in the next seven days, based on risk factors such as age, presence of diabetes, high blood pressure, and symptom duration. This approach is also taken by [113] to determine the probability of the occurrence of kidney disease. The use of Bayesian networks and their ability to reason under uncertainty is discussed in greater detail in Section 5.6.

Another useful aspect of situation prediction is the determination of the prognosis, i.e. expected progression, of a detected disease, although this is poorly explored in the systems. Hussain and Park [108] mention the intention to extend their system in future work to include automated stroke prognosis. In contrast, Yu et al. [124] include a disease progression class in their proposed ontology, representing past diagnoses or potential health risks and their associated times. However, the system does not include any methods to predict the progression of detected conditions.

5.5. Decision Support

Decision support is the natural next step after situation analysis. Based on the detected and predicted situations, targeted support can be offered to mitigate adverse situations and promote favourable health outcomes. Alerts and warnings are used in majority of the systems to warn of potentially dangerous situations and prompt mitigating action. These alerts are often sent to caregivers, doctors, and emergency services depending on severity. However, several systems also take a patient-targeted approach, reminding the monitored individual about medications and exercise [97, 121, 122]. Alerts can also serve to remind users of medications, exercises, and medical tests. For example, the system proposed by Kordestani et al. [113] can remind doctors to order additional laboratory tests when previously taken tests become out of date. A well-documented issue with alerts in the health domain is alert fatigue, a phenomenon in which users become desensitized to alerts due to their frequency [141]. Esposito et al. [101] mitigate this by differentiating between critical and non-critical abnormal situations, with the latter being sent out in a daily summary report email rather than an instantaneous notification for each case.

In addition to alerts, health monitoring systems can also trigger actions in response to adverse situations. For example, the system proposed by Alti et al. [95] triggers the injection of insulin in response to a blood glucose level above a certain threshold, while the system proposed by Hadjadj and Halimi [104] can trigger the opening of a vehicle door. Such systems must be integrated with an actuation device capable of carrying out the action. The system proposed by Titi et al. [121] includes several actuators such as a smoke alarm. Other systems are integrated with actuators capable of sending alarms and making emergency calls [119], or turning off water or gas if detected [122].

Another aspect of decision support is the generation of suggestions and recommendations. Several systems offer recommendations for lifestyle modifications, such as diet and exercise [93, 94, 96, 99, 112, 119, 120], as well as medication [88, 99, 100, 107, 113, 118, 119]. An important factor when choosing appropriate treatment is the side effects of medications and how different medications interact with each other. Ali et al. [92] use drug review websites to collect data on side effects, while Elhadj et al. [100] keep track of medication interactions as well as patient allergies. This information helps doctors prescribe appropriate medications for each patient. Related to recommendations is the ability for the monitored individual to seek out relevant and trusted medical information. For example, the system proposed by Rhayem et al. [119] includes a notification module that allows patients to contact their doctor and receive recommendations and treatments from them.

The use of established medical guidelines is a critical aspect of decision support. This is done by Chatterjee et al. [96], who use medical guidelines for healthy lifestyle management, including nutrition and exercise. Similarly, El-Sappagh et al. [99] use national clinical practice guidelines for the treatment and management of diabetes. In both cases, the guideline information is manually modelled as rules.

5.6. Uncertainty Handling

Given the uncertainty inherent in health decision-making as well as the high likelihood of ambiguity, noise, and missing values in sensor observations, health monitoring systems are greatly enhanced by being able to handle uncertainty. Despite this, only 19 of the systems addressed some aspect of this. The approaches used to handle uncertainty are summarised in Table 8 and discussed in detail in the remainder of this section.

Table 8
Approaches to handle uncertainty and the systems that use them.

Approach	System
Fuzzy logic	Ali et al. [94], Chiang and Liang [97], Esposito et al. [101]; Fenza et al. [102]; Minutolo et al. [117]
Bayesian networks	Kordestani et al. [113], Mcheick et al. [115]
Answer set programming with probabilistic rules	Kordestani et al. [113]
Defeasible logic	Akhtar et al. [91]
Replacing or eliminating missing or invalid sensor data	Ali et al. [92, 93]; Hooda and Rani [106]; Hussain and Park [108]; Reda at al. [89]; Rhayem et al. [119]; Titi et al. [121]
Filtering sensor data	Ali et al. [92, 93]; Garcia-Valverde et al. [103]

5.6.1. Fuzzy Logic

Fuzzy logic is a widely used technique for representing ambiguity and vagueness in sensor data [21]. It is used by five of the systems, making it the most commonly implemented uncertainty handling approach among the systems, besides the preprocessing of sensor data. In fuzzy logic, the truth of a statement is not binary (i.e. either true or false), but can rather be represented in a range from false to true. Therefore, rather than having crisp thresholds for different categories, fuzzy logic allows for values with different degrees of membership for the different categories. The process of converting crisp inputs into fuzzy sets is called fuzzification. For example, heart rate is represented in beats per minute, which can be classified into crisp categories. Generally, a heart rate greater than 100 beats per minute can be categorised as “fast”, a heart rate between 60 and 100 beats per minute can be categorised as “normal”, and a heart rate below 60 beats per minute can be categorised as “slow” [142]. However, with fuzzy logic, any given heart rate value has a certain degree of membership to any of the categories. For instance, a heart rate of 80 beats per minute may have a high degree of membership to the “normal” category (for example, 75%), a lower degree of membership to the “fast” category (for example, 20%), and an even lower degree of membership to the “slow” category (for example, 5%). Fuzzy logic provides a better approach to deal with boundary conditions, e.g. when the heart rate is either 100 or 101, it can be reflected as mostly normal and to a lesser degree fast. Both Ali et al. [94] and Chiang and Liang [97] fuzzify sensor data such as blood pressure and heart rate, as well as attributes such as age and weight. Similarly, Esposito et al. [101] fuzzify the intensity of physical activity, which provides important context for heart rate thresholds. Fenza et al. [102] incorporate fuzzy logic with rules to determine the degree of membership to different situation categories based on different combinations of vital signs, while Minutolo et al. [117] use hybrid rules that incorporate both crisp and fuzzy variables. Fuzzy logic provides a simple but effective mechanism for representing imprecision and vagueness in sensor observations and allows this to be taken into account for more effective situation detection.

5.6.2. *Bayesian Networks*

Bayesian networks are well known for managing uncertainty. They are probabilistic models in the form of directed acyclic graphs that can represent causal relationships among variables in a domain. Bayesian networks have been widely used in the health domain [143]. Kordestani et al. [113] use a Bayesian network for probabilistic diagnosis of acute kidney injury. The Bayesian network models immediate (short-term) and background (long-term) causes of acute kidney injury, as well as its symptoms. They used experts to determine the conditional probabilities of the presence of acute kidney injury given these variables. Similarly, Mcheick et al. [115] represent risk factors for stroke using a Bayesian network.

5.6.3. *Nonmonotonic Reasoning*

Monotonic reasoning holds that the rejection of an earlier conclusion must only be done if the evidence for the conclusion is also rejected. Contrastingly, nonmonotonic reasoning holds that an earlier conclusion can be rejected based on new evidence, even when earlier evidence was valid [144]. This ability to revise conclusions in the face of new evidence is useful in handling uncertainty. Defeasible logic is an example of nonmonotonic reasoning in which there are three kinds of rules: strict rules which can never have exceptions, defeasible rules which are typically true but can have exceptions, and undercutting defeaters which are weak possibilities [144]. Akhtar et al. [91] use defeasible logic to handle inconsistencies in sensor data as well as patient information. Another type of nonmonotonic reasoning is answer set programming (ASP), which is used by Kordestani et al. [113] to automatically customise treatments for each patient. They combine ASP with probability to reason with uncertain knowledge regarding treatment. Using probabilistic ASP rules, their proposed system obtains all possible treatment options for a medical episode and the associated probability of the episode occurring. If the probability of the episode occurring decreases with a particular treatment, then the treatment’s award value is increased. The treatment with the highest award value is ultimately selected by the system.

5.6.4. *Preprocessing Sensor Data*

Uncertainty can stem from various factors in sensor data, including ambiguous or imprecise readings, noise, or missing values caused by sensor malfunctions or network failures [20, 21]. Several systems have addressed the issue of missing values in sensor data. Ali et al. [92, 93] replace them with mean and median values from existing data, while Hooda and Rani [106] replace them using the preceeding value. Rhayem et al. [119] take the approach of removing any missing or unusual values, for example those outside the device measurement ranges. Similarly, Titi et al. [121] and Reda et al. [89] use rules to check whether sensor data falls within the expected minimum and maximum bounds. In their proposed system, Hussain and Park [108] use the Pan-Tompkins algorithm to detect the QRS complex in the ECG. This identifies beats without a QRS complex, which may be premature, missing, or ectopic, and are subsequently eliminated. To deal with noisy data, a few systems use filters to improve signal quality. Ali et al. [92, 93] use a Kalman filter to remove noise, while Garcia-Valverde et al. [103] use a moving average filter for the same purpose.

5.7. *Summary*

This section has provided an in-depth analysis of six key challenges that must be addressed in health monitoring systems, and the role played by semantic technologies in overcoming these challenges. Additionally, non-semantic techniques that are incorporated in the systems have also been discussed. The different aspects related to the challenges are summarised in Table 9, while Table 10 provides a summary of the extent to which the systems address each challenge based on these aspects.

The combined radar chart in Figure 4 provides a visualisation of how well all the systems address the six challenges. Separate radar charts for the individual systems are also available[27]. While context awareness and situation detection are generally well addressed among many of the systems, it is evident that more work is needed to address situation prediction, uncertainty handling, and to a lesser extent, interoperability. Additionally, although two of the systems score highly on decision support, most do not adequately address this challenge.

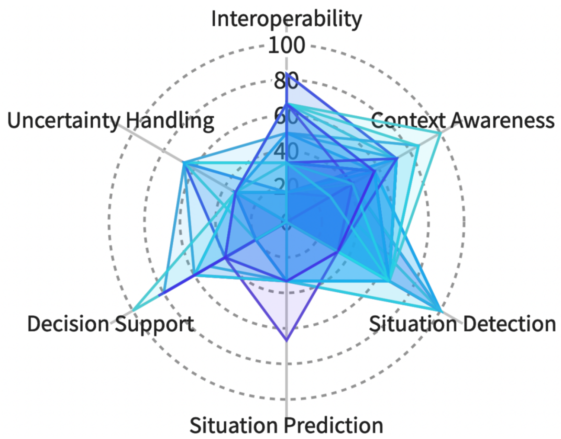

Fig. 4. Combined radar chart showing the extent to which all the systems address the six challenges.

[27]https://public.flourish.studio/visualisation/12454781/

Table 9

Important aspects related to the six key challenges.

Challenge	**Aspects**
Interoperability	1. It is mentioned or illustrated how the system addresses the technical interoperability between the sensors and the rest of the system, e.g. using a gateway device, base unit/station, or established data transmission standards and protocols. 2. The system incorporates established standards or ontologies for describing sensor data, such as the SSN and SAREF ontologies. 3. The system makes use of established health and medical terminologies and nomenclatures such as SNOMED CT, ICT, and ICNP. 4. The system makes use of existing health data standards such as ISO/IEEE 11073, FHIR, and HL7 V2. 5. The system integrates existing health and medical records. 6. The system integrates other sources of data such as weather forecasts, social networks, and other web data.
Context Awareness	1. The system includes and makes use of the concept of location, e.g. GPS coordinates, symbolic locations (“home”, “hospital”, “kitchen”), or geographic regions. 2. The system includes and makes use of the concept of time, e.g. observation timestamps, duration, or time-domain features. 3. The system includes different user roles, such as patient, caregiver, and physician. 4. The system captures information related to an individual’s identity, such as name and address. 5. The system includes and makes use of the concept of activity, e.g. physical activity monitoring or activity recognition. 6. The system incorporates ambient sensor data in addition to physiological data from body sensors. 7. The system includes other types of contextual information, e.g. hardware and networking considerations.
Situation Detection	1. The system can detect deviations or abnormalities in physiological measurements based on historical observations or known thresholds. 2. The system can classify individuals or situations into predefined categories, levels, or states related to health. 3. The system can detect medical conditions or diseases that are currently being experienced.
Situation Prediction	1. The system can predict the occurrence of medical conditions, diseases, or other adverse effects in the future. 2. The system can predict future physiological measurements based on current or historical sensor observations. 3. The system can determine the prognosis of detected diseases.
Decision Support	1. The system sends alerts and notifications for potentially dangerous situations. 2. The system sends reminders, e.g. for medication and exercise. 3. The system sends appropriate recommendations, e.g. for treatment, diet, and exercise. 4. The system is integrated with actuators that can carry out actions in response to situations, e.g. injecting insulin. 5. The system incorporates established clinical practice and medical guidelines. 6. The system provides explanations and can justifies the reasoning behind detected and/or predicted situations as well as any recommendations given. This can be through, for example, visualisations, rules, or queries.
Uncertainty Handling	1. The system is able to handle uncertainty in the situation analysis process, e.g. when diagnosing diseases. 2. The system is able to handle uncertainty in the decision support process, e.g. when determining treatment options. 3. The system is able to handle missing, noisy, or otherwise invalid sensor data.

Table 10
Summary of the extent to which the systems address the six challenges.

#	System	Year	Interoperability	Context Awareness	Situation Detection	Situation Prediction	Decision Support	Uncertainty Handling
1	Akhtar et al. [91]	2022	Low	High	Medium	✗	Low	Low
2	Ali et al. [92]	2021	Medium	Medium	High	Low	Low	Low
3	Ali et al. [93]	2020	Low	Medium	Medium	Low	Medium	Medium
4	Ali et al. [94]	2018	Low	Medium	High	✗	Medium	Medium
5	Alti et al. [95]	2022	Low	High	Medium	Low	Low	✗
6	Chatterjee et al. [96]	2021	Medium	High	Medium	✗	Medium	✗
7	Chiang and Liang [97]	2015	Low	High	Medium	Low	Medium	Low
8	De Brouwer et al. [98]	2022	Medium	Medium	High	Low	Medium	✗
9	El-Sappagh et al. [99]	2019	High	High	Low	✗	Medium	✗
10	Elhadj et al. [100]	2021	High	High	Medium	✗	Medium	✗
11	Esposito et al. [101]	2018	Low	Medium	High	✗	High	Medium
12	Fenza et al. [102]	2012	Low	Low	High	Low	Low	Medium
13	Garcia-Valverde et al. [103]	2014	✗	Medium	Low	✗	Medium	Low
14	Hadjadj and Halimi [104]	2021	Medium	High	Low	✗	High	✗
15	Henaien et al. [105]	2020	Medium	Medium	Low	✗	Medium	✗
16	Hooda and Rani [106]	2020	Low	Low	Medium	✗	Low	Low
17	Hristoskova et al. [107]	2014	Medium	High	Medium	Low	Medium	Low
18	Hussain and Park [108]	2021	Low	Medium	Medium	✗	Medium	Low
19	Ivașcu and Negru [109]	2021	Low	Medium	Low	✗	Low	✗
20	Ivașcu et al. [110]	2015	Low	High	Medium	✗	Low	✗
21	Khozouie et al. [111]	2018	Low	High	Low	✗	Low	✗
22	Kim et al. [112]	2014	Low	Medium	High	✗	Low	✗
23	Kordestani et al. [113]	2021	Medium	Medium	Medium	✗	Medium	Medium
24	Mavropoulos et al. [114]	2021	Low	High	Medium	✗	Medium	✗
25	Mcheick et al. [115]	2016	✗	Medium	Low	Low	Low	Low
26	Mezghani et al. [116]	2015	Low	Medium	Low	✗	Low	Low
27	Minutolo et al. [117]	2016	Low	Medium	High	✗	Low	Low
28	Peral et al. [118]	2018	Medium	Medium	Low	Medium	Medium	✗
29	Reda et al. [89]	2022	Low	High	Medium	Low	✗	Low
30	Rhayem et al. [119]	2021	Medium	High	Medium	Low	Medium	Low
31	Spoladore et al. [120]	2021	Low	Medium	Medium	✗	Medium	✗
32	Stavropoulos et al. [90]	2021	Low	Medium	Medium	✗	Medium	✗
33	Titi et al. [121]	2019	Medium	High	Medium	✗	High	Low
34	Vadillo et al. [122]	2013	Low	High	Low	✗	Medium	✗
35	Villarreal et al. [123]	2014	Low	Medium	Medium	✗	Low	✗
36	Xu et al. [88]	2017	Low	Medium	Medium	✗	Medium	✗
37	Yu et al. [86]	2022	Low	Medium	Low	✗	Medium	✗
38	Yu et al. [124]	2017	Low	Medium	Medium	Low	Low	✗
39	Zhang et al. [125]	2014	Low	Low	Medium	✗	Low	✗
40	Zhou et al. [87]	2022	Medium	Medium	Low	Low	Low	Low

✗ - None of the outlined aspects are addressed by the system
Low - 40% or fewer of the aspects are addressed by the system
Medium - Between 41% and 69% of the aspects are addressed by the system;
High - 70% or more of the aspects are addressed by the system.

6. System Architectures

The architecture of a system can be defined as an abstraction of the system in the form of a set of software structures needed to reason about it [145]. An important concept when discussing system architectures is the architectural style, which defines constraints on the form and structure of an architecture [146]. This is closely related to the architectural pattern, which is a reusable, well-established architectural solution to a recurring design problem [145]. As summarised in Table 4, the systems implement a range of architectural styles and patterns. This section will discuss the architectures of the systems, including how they support the achievement of the six key challenges discussed in Section 5.

6.1. Architectural Styles and Patterns

6.1.1. Layered Architecture

The most common type of architecture among the systems is the layered architecture, implemented in 23 of the systems [88, 89, 91–95, 100–102, 104, 105, 112–116, 120–125]. It is also the most common architectural pattern used in software systems generally [147, 148] and among sensor-based and IoT systems [65, 75]. In this pattern, each layer consists of a group of subtasks, with each group being at a particular level of abstraction [147]. This offers several advantages. It is simple to understand, and the separation of concerns among the different layers makes it easy to test and maintain the systems developed using this architecture [148]. Among the systems, there are variations in the number of layers and their functionality. However, a typical first layer is the data collection layer, which may also be referred to as the sensing or physical layer. It is in this layer that sensor devices and the data they collect are represented in the architecture. For health monitoring systems, this is usually in the form of a BSN; however ambient sensors and other data sources can be included in this layer. Other typical layers include a data storage layer in which data is securely stored; networking layer which manages data communication and transmission in the system; inference and data analysis layer, in which the raw data is processed and analysed to derive important insights; and finally, presentation layer in the form of a user interface where individuals and in some cases, their clinicians and caregivers, can receive visualisations and alerts.

6.1.2. Modular Architecture

Similar to the layered architecture is the modular architecture, in which the system is subdivided into modules or subsystems. This is the second most common architectural pattern among the systems, with some kind of modular pattern implemented in 16 of the systems [86, 87, 90, 96–99, 106, 108–111, 114, 117, 119, 125]. Modular and layered architectural patterns can be used concurrently. For example, in the system proposed by Zhang et al. [125], the client management module has a middleware with a layered architecture. Additionally, Meyer and Webb [149] advocate for the modularity of layered architectures, in which each layer consists of a modular set of components with a single function or purpose. Given the propensity of layered architectures towards monolithicity, making them less agile and difficult to scale and deploy [148], ensuring modularity in each layer is advised. This is implemented by Mavropolous et al. [114], whose architecture has 3 levels (layers), with each containing specific modules. For example, the sensors management level contains a data analysis module, while the communication understanding level contains a natural language processing module.

6.1.3. Service-Oriented Architecture

Another well-known architectural pattern is the service-oriented architecture, a distributed pattern in which system components provide and consume services [145]. In service-oriented architectures, the different aspects of the challenges can be achieved using specialised services. For example, Hristoskova et al. [107] implement services such as a notification service to generate alerts (decision support) and a user location service to localize specific users (context awareness). While the service-oriented architectural pattern is powerful and offers a high level of abstraction, it is often overly complex and difficult to understand [148]. A way of mitigating these issues is to implement services in a layered architecture, as is done in several other systems [88, 95, 102, 116]. Additionally, agents can be used to effectively manage services, as is the case in the systems proposed by Alti et al. [95] and Fenza et al. [102].

6.1.4. Agent-Based Architecture

Among the systems, seven implement an agent-based architecture. Six of these systems use a multi-agent architecture [91, 95, 102, 109, 110, 122] while one implements a single-agent architecture [114]. Multi-agent systems are characterised by the existence of more than one agent acting autonomously within the system. Typically, each agent manages a particular aspect of the system, which enables decentralisation, efficiency, and scalability. For example, Alti et al. [95] implement situation detection using a situation reasoning agent and a diseases classifying agent, while Ivascu and Negru [109] and Ivascu et al. [110] have notification and alert agents that enhance decision support. Similarly, the system proposed by Vadillo et al. [122] has a sensor validation agent to verify sensor observations thereby managing uncertainty in sensor data, a location agent to mange user locations thereby contributing to context awareness, and a medication agent to oversee the administering of medication, which contributes to decision support. Among the multi-agent systems that incorporate a service-oriented architecture, agents are instrumental in managing the complexity of the services. Both Alti et al. [95] and Fenza et al. [102] use agents to handle service discovery and selection. Agents can also enhance decision support by interacting directly with users of the system. This is demonstrated by Mavropoulos et al. [114], who use a smart virtual agent capable of dialogue to communicate with doctors and support their decision-making.

6.2. Proposed Reference Architecture

Based on an analysis of the systems as well as an overview of general sensor-based systems, a reference layered architecture for personal health monitoring systems is presented in Figure 5. The data layer includes the sources of relevant health data, such as body and ambient sensors, medical records, and the web. It also handles protocols and standards related to data transmission, as well as the storage of data in databases. The analysis layer provides functionality for the analysis of collected data, using approaches such as semantic technologies, rules, queries, machine learning, Bayesian networks, and fuzzy logic. Finally, the presentation layer deals with the way the system interacts with its users. This is typically through web and mobile applications that display visualisations of data and generate alerts, reminders, and other notifications. This architecture is consistent with the layered architectures proposed in related reviews [9, 66, 68, 69, 75], with the exception that other sources of health data other than sensors are included in the data collection layer. Additionally, our proposed reference architecture highlights the layers in which each of the six key challenges are typically addressed.

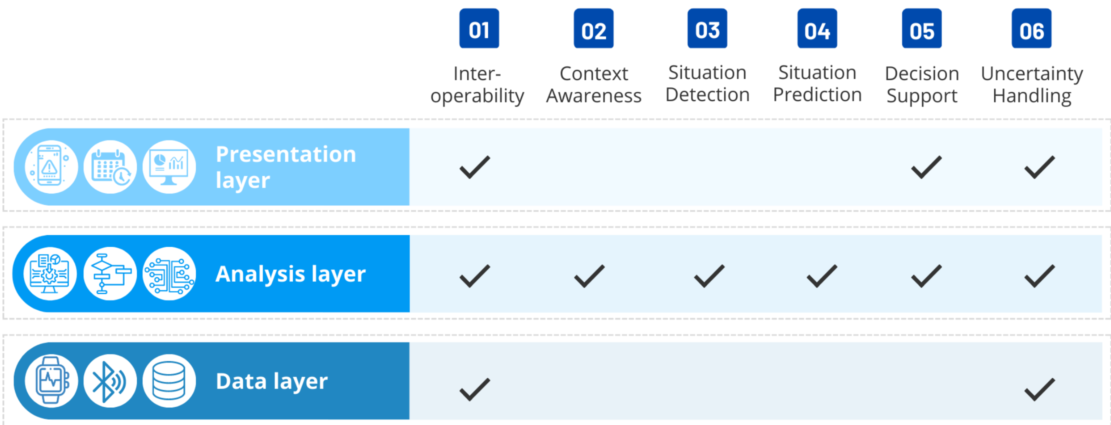

Fig. 5. Reference layered architecture for sensor-based personal health monitoring systems.

7. Methodology and Evaluation

Research and development methodologies play a crucial role in the development of robust and effective systems, which must also be sufficiently evaluated to ensure optimal functionality. This section discusses the methodology and evaluation approaches used in the systems, beginning with an exploration of the sources of data. We then discuss the tools used for system development, with a focus on semantic languages, software, and data stores. Next, we highlight the methodologies used to develop the semantic technologies. We conclude by discussing the approaches used to evaluated the semantic technologies and the systems as a whole.

7.1. Data Collection and Sources

The data collection methodology varies among the systems. Many systems used existing datasets from publicly available repositories such as PhysioNet[28] and the University of California, Irvine (UCI) machine learning repository [29]. These systems and the datasets they use are summarised in Table 11. A smaller number of the systems used data collected from participants rather than existing data. For example, Ali et al. [94] collected data from 44 diabetes patients, while Esposito et al. [101] collected data from 10 healthy volunteers. Other systems that used this approach are those proposed by Hristoskova [107], Stavropoulos et al. [90], Vadillo et al. [122] and Villareal et al. [123]. Hussain and Park [108] took a hybdrid approach by collecting data from participants and combining it with an existing dataset to form a new one. Another approach was to simulate or manually generate the data. This was explored by Chatterjee et al. [96], who simulated sensor, interview, and questionnaire data of four dummy participants. Mchiek et al. [115] similarly generated 513 records of data. A significant number of the systems indicated the types of data and sensors supported by the systems, but did not mention the source of the data. It is unclear whether these systems were validated using actual sensor data, beyond a theoretical validation of the system functionality. Table 12 includes a summary of the sources of data used in the systems.

Table 11

Existing datasets used.

System	Dataset	Source
Ali et al. [92]	Pima Indians diabetes dataset Multiparameter Intelligent Monitoring in Intensive Care (MIMIC-II) Drug review dataset	UCI ML Repository PhysioNet UCI ML Repository
Ali et al. [93]	Heart disease dataset (Cleveland, Hungary)	UCI ML Repository
Garcia-Valverde et al. [103]	PAMAP2 Physical Activity Monitoring dataset	UCI ML Repository
Hadjadj and Halimi [104]	Vital signs of 15 Volunteers	Figshare
Henaien et al. [105]	Vital signs dataset	University of Queensland
Hooda and Rani [106]	Pima Indians diabetes dataset Heart disease dataset (Cleveland)	UCI ML Repository UCI ML Repository
Hussain and Park [108]	Single-channel ECG dataset recorded using the Biopac MP160 system	Chungnam National University Hospital
Ivașcu and Negru [109]	Mobile health dataset	UCI ML Repository
Kordestani et al. [113]	Chronic kidney disease dataset Dermatology dataset	UCI ML Repository UCI ML Repository
Mavropoulos et al. [114]	Heterogeneity Human Activity Recognition dataset CoNNL2003 dataset	UCI ML Repository Sang et al. [150]
Peral et al. [118]	Diabetes dataset	UCI ML Repository
Rhayem et al. [119]	Various undisclosed datasets	PhysioNet
Yu et al. [86]	Undisclosed dataset	Children's Hospital, Zhejiang University School of Medicine

7.2. Development Languages, Software, and Semantic Data Stores

Various languages, frameworks, and libraries were used to develop the semantic technologies in the systems. Among the systems that incorporated ontologies, Protégé[30] is most commonly cited as the ontology development

[28] https://physionet.org/
[29] https://archive.ics.uci.edu/ml/index.php
[30] https://protege.stanford.edu/

platform of choice, used in about half of the systems. Protégé is an ontology editor that supports the latest OWL and RDF specifications. Another commonly used platform is Apache Jena[31], a Java framework for building Semantic Web and Linked Data applications, used in 15 of the systems. Both Protégé and Jena are free and open source. When it comes to the Semantic Web languages, SWRL is the most commonly used rule language among the systems. However, Jena includes a general purpose rule-based reasoner which is used by Chiang and Liang [97], Garcia-Valverde et al. [103], and Kim et al. [112]. Stavropoulos et al. [90] used Shapes Constraint Language (SHACL)[32] to create rules, while Kordestani et al. [113] used Drools[33], a business rule management system. Programming languages can also be used to configure rules, as was done by Khozouie et al. [111] using Java. For queries, a majority of the systems used SPARQL, with some also using Fuseki[34], a SPARQL server that is part of Jena, to publish their SPARQL endpoints. De Brouwer et al. [98] use C-SPARQL, an extension of SPARQL that supports continuous queries. For storage of the semantic technologies, Mavropoulos [114] and Stavropoulos et al. [90] used Ontotext GraphDB[35], while Spoladore et al. [120] used Stardog[36]. Both of these are enterprise semantic databases. A summary of the semantic technology development languages and tools used by the systems can found in Table 12.

7.3. Development Methodologies

The use of a development methodology can streamline the process of developing semantic technologies. In particular, the literature on ontology development methodologies is quite rich, with a large number of established methodologies proposed [151, 152]. There have also been several proposed approaches towards developing knowledge graphs [153] and ensuring the quality of linked data [154, 155]. Despite this, most of the systems did not report the use of a methodology in the development of the semantic technologies. However, a small number of systems mentioned using a particular methodology. For example, Hadjadj and Halimi [104] used the NeOn framework [156], a scenario-based methodology for building ontologies, while Titi et al. [121] used an existing case-based ontology engineering methodology [157]. Although not a development methodology, Peral et al. [118] used the SemanTic Refinement of Ontology MAppings (STROMA) [158] approach for aligning corresponding concepts between different ontologies.

7.4. Evaluation Approaches

The evaluation approaches used by the systems are summarised in Table 12, with case-based evaluation being the most common approach used by 26 of the 40 systems. 17 of these are evaluated through use case scenarios, which generally describe the sequence of events when a user interacts with the system [87, 90, 97–100, 103, 104, 110, 111, 113, 115, 116, 120, 122, 125]. Nine systems are evaluated using case studies, which are similar to use case scenarios but are more extensive and detailed [88, 91, 95, 101, 102, 105, 117, 118, 123]. Beyond use case scenarios and case studies, eight authors compared their systems with existing ones, showing how they performed against the state of the art [88, 93, 94, 99, 108, 109, 114, 119]. Additionally, a few authors used simulation as a means to investigate the system functionality. For example, Akhtar et al. [91] used Netlogo, a multi-agent modelling platform, to simulate the use of their system. Chiang and Liang [97] used a fuzzy logic simulation tool to validate their fuzzy inference module. Ivașcu and Negru [109] simulated the system functionality by using each subject in the dataset as the target user, while Reda et al. [89] used a web portal with sample data for testing purposes.

A number of systems were evaluated based on quality of service metrics. For example, Esposito et al. [101] and Vadillo et al. [122] used the Architecture-Level Modifiability Analysis (ALMA) method to evaluate the potential costs associated with modifying their systems, such as by adding more sensors. Similarly, Alti et al. [95] evaluated their system based on execution time, optimality, application's lifetime and number of discovered services.

[31]https://jena.apache.org/
[32]https://www.w3.org/TR/shacl/
[33]https://www.drools.org/
[34]https://jena.apache.org/documentation/fuseki2/
[35]https://graphdb.ontotext.com/
[36]https://www.stardog.com/

Table 12

Summary of data sources, development tools, and evaluation approaches and metrics used by the systems.

#	System	Data Sources	Semantic Technologies ǀ Development Tools, Languages, & Data Stores	Evaluation Approaches	Evaluation Metrics/Criteria
1	Akhtar et al. [91]	None mentioned	Ontology ǀ Protégé	Case study; System simulation	None mentioned
2	Ali et al. [92]	Existing datasets; Web data	Ontology ǀ OWL; Protégé	ML model performance; Ablation study	Accuracy; Precision; Recall; RMSE; MAE
3	Ali et al. [93]	Existing datasets	Ontology ǀ OWL; Protégé; SWRL	ML model performance; Ablation study	Accuracy; Precision; Recall; F-score; RMSE; MAE
4	Ali et al. [94]	Participants	Ontology ǀ Jena; OWL; Pellet; Protégé; SPARQL; SWRL	Comparison with SOTA; Expert evaluation of system; Ontology validation	Accuracy; Precision; Recall; F-score
5	Alti et al. [95]	None mentioned	Ontology ǀ Jena; Protégé; SWRL	Case study; Comparison with SOTA	Execution time; Optimality; Application lifetime; No. of discovered services
6	Chatterjee et al. [96]	Simulated	Ontology ǀ Fuseki; Jena; HermiT; OWL; Protégé; RDF; SPARQL; SWRL	Ontology validation	Ontology reasoning time
7	Chiang and Liang [97]	None mentioned	Ontology ǀ Jena; Protégé; RDF	Use case scenarios; System simulation	None mentioned
8	De Brouwer et al. [98]	None mentioned	Ontology ǀ C-SPARQL; Jena; RDF	System queries; Use case scenarios	None mentioned
9	El-Sappagh et al. [99]	None mentioned	Ontology ǀ HermiT; OWL; Pellet; Protégé; SPARQL; SWRL	Ontology validation; Comparison with SOTA; Comparison with expert opinion; Use case scenarios	Correctness; Completeness; Extensibility; Conciseness; Organisational fitness
10	Elhadj et al. [100]	None mentioned	Ontology ǀ Fuseki; OWL; Pellet; Protégé	Use case scenarios	None mentioned
11	Esposito et al. [101]	Participants	Ontology ǀ OWL; Pellet; Protégé	Case study; ALMA method; Ontology validation	None mentioned
12	Fenza et al. [102]	None mentioned	Ontology ǀ OWL; SPARQL	Case study; Comparison with logic-based matching	Precision; Recall
13	Garcia-Valverde et al. [103]	Existing dataset	Ontology ǀ Jena	Use case scenario	Accuracy; Precision; F-score
14	Hadjadj and Halimi [104]	Existing dataset	Ontology ǀ Jena; OWL; Protégé; SPARQL; SWRL	Use case scenario; Comparison with expert opinion	Similarity between system and expert opinion
15	Henaien et al. [105]	Existing dataset	Ontology ǀ Protégé; SWRL	Case study	None mentioned
16	Hooda and Rani [106]	Existing datasets	Ontology ǀ Jena; OWL; Pellet; Protégé; RDF; SPARQL; SWRL	Ontology validation	None mentioned
17	Hristoskova et al. [107]	Participants	Ontology ǀ OWL; Pellet; SWRL	Expert evaluation; User evaluation; Ontology validation	Performance; Scalability
18	Hussain and Park [108]	Participants; Existing Dataset	Ontology ǀ OWL; Protégé; RDF	Comparison with SOTA	AUC; Accuracy; Precision; Recall; Neg. predictive value
19	Ivașcu and Negru [109]	Existing dataset	Ontology ǀ Fuseki; Jena; Protégé; SPARQL	Comparison with SOTA; System simulation	Accuracy; Precision; Recall; F-score
20	Ivașcu et al. [110]	None mentioned	Ontology ǀ Jena; Protégé	Use case scenarios	None mentioned
21	Khozouie et al. [111]	None mentioned	Ontology ǀ OWL; Pellet; Protégé	Use case scenario; Ontology validation; Expert evaluation	None mentioned
22	Kim et al. [112]	KMA	Ontology ǀ Jena; OWL; Protégé	Ontology validation; User evaluation	Precision; Recall; F-score; Likert score
23	Kordestani et al. [113]	Existing datasets	Ontology ǀ None mentioned	Comparison between BN and ML diagnosis; Use case scenarios	F-score
24	Mavropoulos et al. [114]	Existing datasets	Ontology ǀ GraphDB; OWL; SPARQL	Comparison with SOTA; End user evaluation	Accuracy; Precision; Recall; F-score; Likert scale
25	Mcheick et al. [115]	Simulated	Ontology ǀ None mentioned	Use case scenarios	Adaptability
26	Mezghani et al. [116]	None mentioned	Ontology ǀ Fuseki; RDF; SPARQL	Use case scenario	None mentioned
27	Minutolo et al. [117]	None mentioned	Ontology ǀ None mentioned	Case study	None mentioned
28	Peral et al. [118]	Web data; Existing datasets	Ontology ǀ None mentioned	Case study	Similarity between actual and predicted values
29	Reda et al. [89]	None mentioned	Linked Data; Ontology ǀ OWL; RDF; RML; SPARQL; SWRL	System simulation	Not mentioned
30	Rhayem et al. [119]	Existing datasets	Ontology ǀ Jena; OWL; SPARQL; SWRL	Comparison with SOTA; Ontology validation	F-score; Precision; Recall; Response time; Ontology coverage
31	Spoladore et al. [120]	None mentioned	Ontology ǀ OWL; Protégé; SPARQL; Stardog; SWRL	Use case scenarios	None mentioned
32	Stavropoulos et al. [90]	Participants	Ontology ǀ GraphDB; OWL; SHACL; SPARQL	Use case scenarios; Focus group with clinicians	Scalability; Likert scale
33	Titi et al. [121]	None mentioned	Knowledge graph; Ontology ǀ Jena; Pellet; Protégé; RDF; SPARQL; SWRL	System queries	None mentioned
34	Vadillo et al. [122]	Participants	Ontology ǀ Jena; OWL; Pellet; Protégé;	Use case scenarios; Ontology validation	Processing time
35	Villarreal et al. [123]	Participants	Ontology ǀ None mentioned	Case study; ALMA method; User evaluation	Response time; Usability; Recommendation suitability
36	Xu et al. [88]	None mentioned	Linked data; Knowledge graph ǀ SPARQL	Case study; Comparison with SOTA	None mentioned
37	Yu et al. [86]	Existing dataset	Knowledge graph ǀ None mentioned	ML model performance; Use case scenarios	AUC; CCM criteria
38	Yu et al. [124]	None mentioned	Ontology ǀ Jena; OWL; RDF; SPARQL; SWRL	System queries	None mentioned
39	Zhang et al. [125]	None mentioned	Ontology ǀ OWL; RDF; SWRL	Use case scenario	None mentioned
40	Zhou et al. [87]	None mentioned	Knowledge graph ǀ None mentioned	Use case scenario	None mentioned

ALMA - Architecture-Level Modifiability Analysis; AUC - Area Under the Curve; BN - Bayesian Network; CCM - Chronic Care Model; KMA - Korea Meteorological Administration web service; MAE - Mean Absolute Error; ML - Machine Learning; OWL - Web Ontology Language; RDF - Resource Description Framework; RML - RDF Mapping Language; RMSE - Root Mean Square Error; SHACL - Shapes Constraint Language; SOTA - State of the Art; SPARQL - SPARQL Protocol and RDF Query Language; SWRL - Semantic Web Rule Language

Yu et al. [86] evaluated their system using the Chronic Care Model (CCM), an established framework for chronic care management that includes criteria such as system design, self-management support, and decision support. The systems proposed by Hristoskova et al. [107], Kim et al. [112], Mavropoulos et al. [114], Stavropoulos et al. [90], and Villarreal et al. [123] were evaluated using user studies with patients or clinicians, with Likert scales typically used to scale the user feedback. Expert validation was also used to evaluate the systems, with the aim of ensuring maximum similarity between the system output and expert opinion. This approach was taken by Ali et al. [93], El-Sappagh et al. [99], Hadjadj and Halimi [104], Hristoskova et al. [107] and Khozouie et al. [111]. Additionally, a number of systems used query-based validation, where the system is validated by checking the answers to SPARQL queries.

In addition to the overall system, the system components were also evaluated. Inconsistencies in ontologies can be detected using ontological reasoners, which check whether there are contradictions in class hierarchies or class instances [5]. Reasoners such as HermiT [159] and Pellet [160] were used in many of the systems to evaluate the structural consistency of ontologies [94, 96, 99–101, 106, 107, 111, 121, 122]. Additionally, the ontology evaluation frameworks OntOlogy Pitfall Scanner! (OOPS!) [161] and OQuaRE [162] were used by El-Sappagh et al. [99] and Rhayem et al. [76] respectively. Some systems also evaluated the effect of different components within the same system through ablation studies. For example, Ali et al. [92] tested the performance of their Bi-LSTM model for classifying healthcare data while using an ontology and without using an ontology. The results showed an increase in the accuracy of the model when combined with an ontology. Similarly, Ali et al. [93] tested compared the performance of their proposed ensemble deep learning model with and without feature selection. Additionally, systems that implemented machine learning used well-known metrics such as accuracy, precision, recall, F-score, and mean square error to evaluate the machine learning models.

8. Conclusions and Future Research Directions

This study has analysed the landscape of sensor-based personal health monitoring systems that incorporate semantic technologies. Based on an understanding of the issues arising from using sensor data and the essential functionalities necessary for reliable health monitoring, we identified six key challenges that such systems must address. In a systematic process, we selected 40 systems representing the state of the art in the field, and critically evaluated them according to the six identified challenges. Figure 6 shows a map outlining the current state of the field. In the remainder of this section, the inadequacies and limitations in current systems will be highlighted, paving the way for opportunities for future research.

Our findings show that four of the six identified challenges remain poorly addressed among the systems: situation prediction, uncertainty handling, and, to a lesser extent, interoperability and decision support. Most of the systems included in this study do not adequately address the challenge of situation prediction, as they are incapable of predicting health risks or giving insight into how detected conditions may progress with time. In order to achieve the vision of precision health, it is important for health monitoring systems to go beyond detecting current health states and move towards the anticipation and mitigation of adverse health states. Uncertainty handling is similarly poorly implemented or not addressed at all in majority of the systems. While some of the systems consider the impact of sensor limitations such as noise and missing values, most do not address the inherent uncertainty present in situation analysis and decision support in the health domain. This hinders their ability to perform reliably when faced with ambiguous data or vague or limited knowledge, thus reducing their trustworthiness and dependability. Both situation prediction and uncertainty handling can be enhanced by a combination of techniques, as suggested by Behera et al. [81], such as machine learning and Bayesian networks. Few of the systems take such an approach, with the majority using solely rule-based reasoning.

Additionally, we found that less than a third of the systems take advantage of established sensor ontologies such as SOSA/SSN, thereby limiting the expressiveness of their descriptions of sensors and, importantly, sensor data. This results in less effective querying of and reasoning on sensor data, which in turn negatively impacts situation analysis. In addition, while some systems incorporate established medical terminologies such as SNOMED CT and ICD, nearly all the systems fail to consider existing health data standards, such as FHIR. This limits the extent to which such systems can use existing health data such as medical records. There is also significant room for improvement

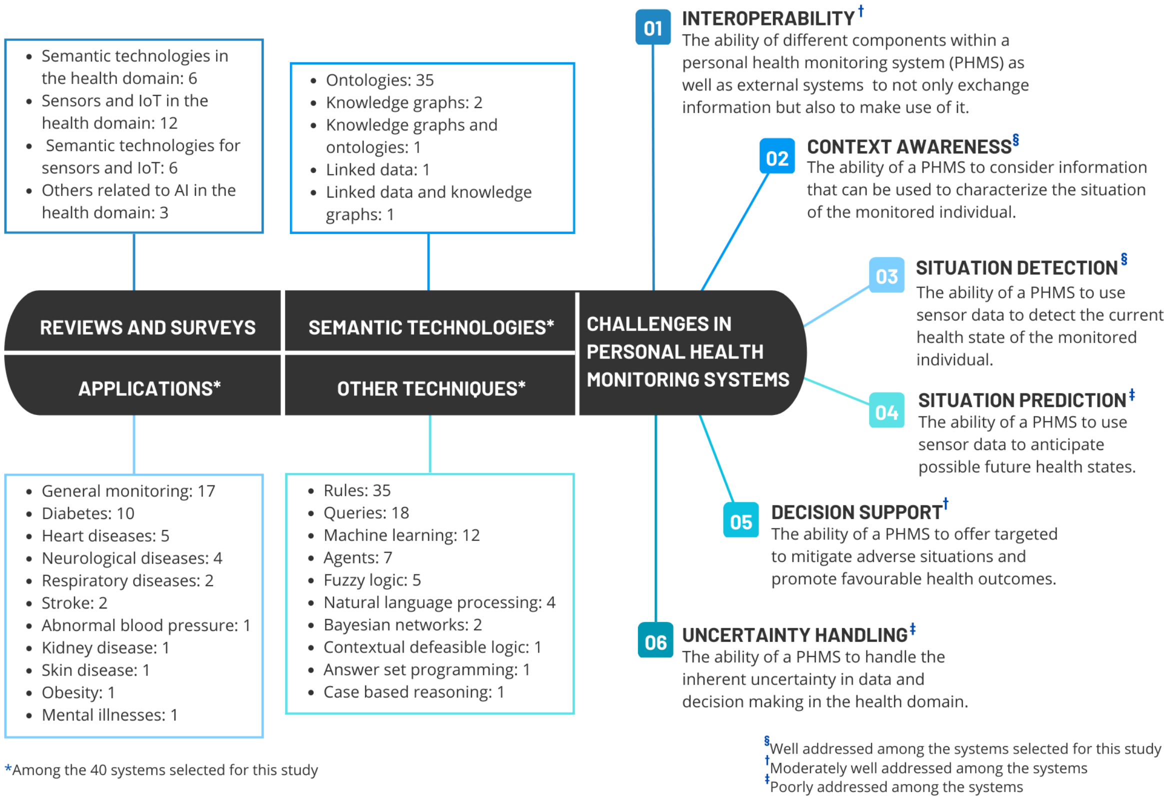

Fig. 6. Map showing the current state of the field.

in addressing the challenge of decision support. While most of the included systems incorporate alerts to warn of hazardous situations, many do not offer recommendations or reminders for medication or lifestyle factors such as diet and exercise. Similarly, very few of the systems report using established medical guidelines. Such guidelines provide a sound justification for any recommendations made, thereby enhancing the trustworthiness of the systems. This is related to explainability, which is gaining traction as a pivotal aspect of decision support in AI-driven health systems [60]. Among systems that incorporate machine learning models that are known to be opaque, such as neural networks, semantic technologies have been shown to be effective in increasing their explainability [163].

With regards to the methodology and evaluation, we found that a number of systems did not report the data collection methods or sources. It can be assumed that such systems may not have been validated using real-world data, which casts doubts on the claims made regarding the system functionality and performance. To mitigate this, researchers should clearly indicate which data was used to validate their systems, including how the data was collected, who it was collected from, and the devices that were used. Wherever possible, researchers should include the system components such as data and code as publicly accessible supplementary material in order to enhance reproducibility and verifiability. Additionally, as was found in the review by Haque et al. [60], most systems have not yet been evaluated in real-world settings. While this is to be expected in an emerging area, going forward it is imperative for more systems to be evaluated in real-world settings, so that practical challenges and user feedback can be identified early on and considered in future system proposals. This feedback loop is essential for undertaking further research into personal health monitoring systems that fully harness the potential of semantic technologies.

This study also highlights the fact that most personal health monitoring systems are disease-specific, which limits their generalisability. Semantic technologies have the potential to be extendable, allowing for the addition of knowledge as it evolves, thus making them suitable to support general monitoring. Additionally, a number of the systems do not take into account factors such as diet, exercise, and other determinants of health. The next generation of personal health monitoring systems must be more holistic, focusing not only on disease but also on overall wellness. This includes the monitoring of emotional and mental states, which has been shown to be linked to physical health [164]. Such information can be represented using semantic technologies, including ontologies [165] and knowledge graphs [166]. The four inadequately addressed challenges, together with the need for more general and holistic health monitoring, present interesting and important directions for future research in the field.

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