



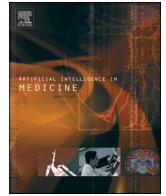
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Ubiquitous and smart healthcare monitoring frameworks based on machine learning: A comprehensive review

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ABSTRACT

During the COVID-19 pandemic, the patient care delivery paradigm rapidly shifted to remote technological solutions. Rising rates of life expectancy of older people, and deaths due to chronic diseases (CDs) such as cancer, diabetes and respiratory disease pose many challenges to healthcare. While the feasibility of Remote Patient Monitoring (RPM) with a Smart Healthcare Monitoring (SHM) framework was somewhat questionable before the COVID-19 pandemic, it is now a proven commodity and is on its way to becoming ubiquitous. More health organizations are adopting RPM to enable CD management in the absence of individual monitoring. The current studies on SHM have reviewed the applications of IoT and/or Machine Learning (ML) in the domain, their architecture, security, privacy and other network related issues. However, no study has analyzed the AI and ubiquitous computing advances in SHM frameworks. The objective of this research is to identify and map key technical concepts in the SHM framework. In this context an interesting and meaningful classification of the research articles surveyed for this work is presented. The comprehensive and systematic review is based on the "Preferred Reporting Items for Systematic Review and Meta-Analysis" (PRISMA) approach. A total of 2540 papers were screened from leading research archives from 2016 to March 2021, and finally, 50 articles were selected for review. The major advantages, developments, distinctive architectural structure, components, technical challenges and possibilities in SHM are briefly discussed. A review of various recent cloud and fog computing based architectures, major ML implementation challenges, prospects and future trends is also presented. The survey primarily encourages the data driven predictive analytics aspects of healthcare and the development of ML models for health empowerment.

Summary of important acronyms

Acronym	Definition
5G	Fifth Generation
AI	Artificial Intelligence
AAL	Ambient Assisted Living
ACM	Association for Computing Machinery
ANN	Artificial Neural Network
BBN	Bayesian Belief Network
BP	Blood Pressure
CC	Cloud Computing
CD	Chronic Disease
CNN	Convolutional Neural Network
CVD	Cardiovascular Disease
DBN	Deep Belief Network
DC	Data Center

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DL	Deep Learning
DT	Decision Tree
ECG	Electrocardiography
EHM	Elderly Healthcare Monitoring
ENN	Elman Neural Network
EWS	Early Warning Score
FC	Fog Computing
GAN	Generative Adversarial Network
HRRM	Hybrid Real-time Remote Monitoring
HoF	Hospital of the Future
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
IoMT	Internet of Medical Things
k-NN	k-Nearest Neighbor
LR	Logistic Regression

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LSTM	Long Short Term Memory
MDPI	Multidisciplinary Digital Publishing Institute
ML	Machine Learning
M-Health	Mobile Health
NB	Naive Bayes
PCA	Principal Component Analysis
PDO	Probability of Disease Outbreak
PHS	Panic Health Status
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QoS	Quality of Service
RBM	Restricted Boltzmann Machine
RF	Radio Frequency
RFID	Radio Frequency Identification
RNN	Recurrent Neural Network
RPM	Remote Patient Monitoring
SHM	Smart Healthcare Monitoring
SPMR	Smart Patient Monitoring and Recommendation
SVM	Support Vector Machine
WBAN	Wireless Body Area Network
WPM	Wearable Patient Monitoring
WSN	Wireless Sensor Network

1. Introduction

1.1. Background

Chronic diseases account for approximately 74 % of all fatalities worldwide, according to the most recent statistics (2019). During few decades, life expectancy has increased significantly due to modern health care facilities. However, the stakeholders in the healthcare domain, such as patients, doctors, clinicians, caregivers and devices often need assistance and regular monitoring. In such cases, an autonomous supporting system may be helpful. Machine Learning (ML) and computing is on the edge to transform every domain including healthcare. The emerging paradigms of the Internet of Things (IoT), Ubiquitous Computing, Cloud Computing (CC), and analytics have the potential to implement Smart-Health Knowledge Systems. These

systems host novel links between a person's natural habitat, his body, and the Internet with the goal of producing and managing “participatory” medical knowledge.

The monitoring of patients with Smart Healthcare Monitoring (SHM) systems aims at various categories of patients, such as post-surgery patients, elderly patients, neonates, patients with disabilities and with chronic illnesses. All such patients have conditions that need to be monitored with SHM systems remotely and in real time. The technological revolution in healthcare informatics has been predicted long ago and is underway as the use cases shown in this Fig. 1 make it clear. The major use-cases [1,2] are depicted in Fig. 1. According to the authors [1], monitoring, offering assistance, disease diagnosis, self-care and management, wellness, customized healthcare, and quantitative and/or qualitative facility improvement are among the current use-cases of emerging IT. New use-cases [3] are continuously emerging to handle the immediate need for inexpensive, accessible care.

The SHM has been enabled by various tools that uninterruptedly monitor vital values/signs, manages treatments automatically, follow real time information and self-managed treatment of patient. The new term coined for fusion of medical devices, healthcare applications and computer networks is the Internet of Medical Things (IoMT) [4]. Fig. 2, displays a substantial picture of how various healthcare tools/technologies are convened together to form IoMT. SHM systems are an imminent solution for addressing many of the challenges by enablement of various technologies between the patients and their care delivery environment. However, the SHM systems are utilizing medical tools and applications along with networking and intelligent technologies. The healthcare industry has been revolutionized by the inclusion of IoT [5], Wireless Body Area Network (WBAN) [6–8], Mobile communication, Edge [9,10] and Ubiquitous computing. Furthermore, in the current situation, certain domains, such as Big Data analysis, CC [11], Ubiquitous Computing, and M-Health, also show a key role in this field. Also, the application of ML and Artificial Intelligence (AI) to big data provides actionable insights to improve healthcare delivery [12,13]. Although there are many instances in which AI can perform healthcare tasks as well or better than humans [14].

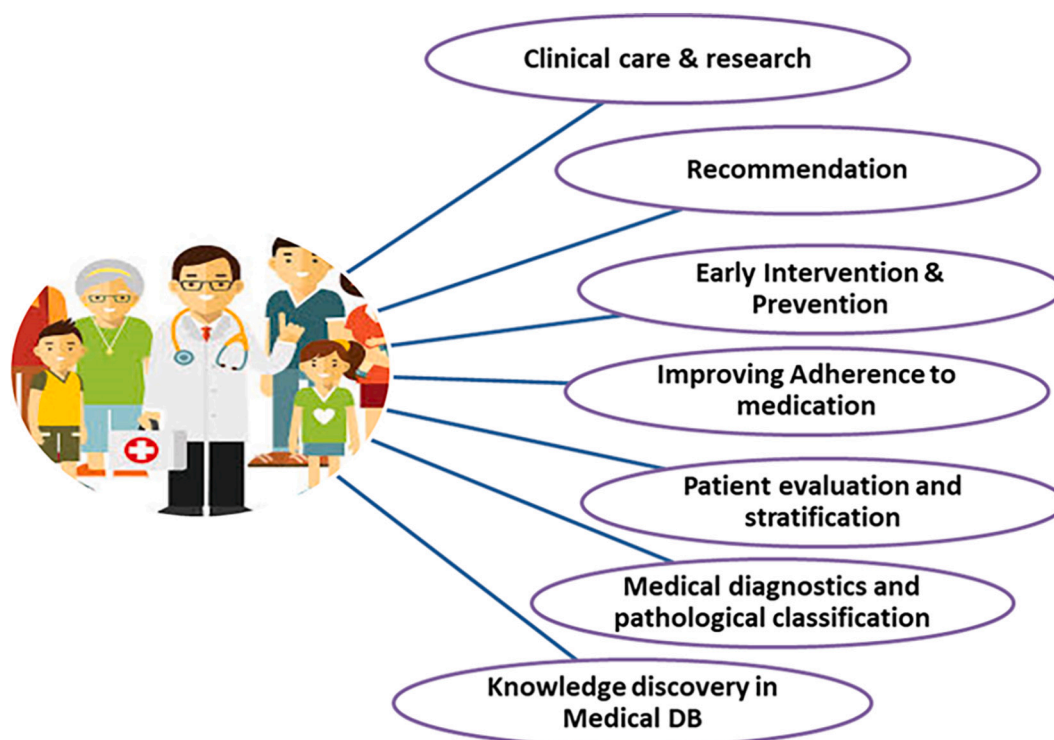


Fig. 1. Healthcare informatics use-cases.



Fig. 2. IoMT at a glance.

The aim of SHM systems and good healthcare facilities includes:

- o Providing as much comfort as possible to all patients.
- o Providing freedom of activity and mobility in 'personal care delivery environment' and at home.
- o Early detection of disease risks and symptoms.
- o Timely initiation of preventive care for slowing down the disease progression.
- o Advantages of staying at home rather than in a high-priced hospital room.
- o Lowering the treatment costs and enhance patient satisfaction.
- o Support in routine activities.
- o Keeping an eye on the patient's health and offering urgent care and assistance, as needed, while advising the paramedics who are on the scene.

1.2. Role of machine learning in healthcare

The SHM has intensely altered the vision to healthcare. The embedded, wearable and ubiquitous IoT sensors can gather data in real-time, comprising patient contexts such as mobility. The ML or Deep Learning (DL) methods can be applied to the collected data to discover unseen patterns and information in the data and for tracking the patient's health to diagnose and notify about critical conditions.

ML a sub-domain of AI applies mathematical and scientific techniques for learning and deriving new insights from the data thus making healthcare applications more intelligent. Also, the cognitive science is the blend of various scientific fields that employs AI, ML, and other mathematical and scientific techniques for learning and deriving new insights. It is playing a substantial role in making applications more intelligent. Latif et al. [15], in their article have discussed how the 5G and its concomitant technologies along with AI and ML have the potential to revamp the health care system. Cognitive technologies are advancements in computing that mimics some facet of human deliberation processes on a larger scale.

We expect to see a stronger convergence between AI, ML and SHM frameworks as technology advances. Data from "Electronic Health Records" (EHR) can aid in the detection of infection patterns and the identification of people at risk before they develop symptoms. Using ML

and AI to drive these analytics can improve their accuracy and give healthcare providers with faster, more accurate alerts. ML algorithms and their ability to synthesize very complex information may open up new avenues for tailoring medicines to a person's genetic composition. The big-data generated by medical devices are a perfect fit with ML capabilities for disease diagnosis and emergency care for patients. This system enables caregivers and healthcare professionals to find patients at high risk and administer special care. AI has brought confidence in SHM and reduced the human error factors. However, telemedicine via IoMT generates vast amounts of data, which must then be transmitted, analyzed and stored. Therefore, ML algorithms need to be extended on big-data for faster analysis, which is possible on scalable CC platforms.

Nevertheless, critical healthcare infrastructure requires more robust architectures for higher accuracy, availability and real-time responses. So, here is the need for advanced cloud design including edge intelligence and fog computing (FC) [16].

1.3. Motivation

During the COVID-19 pandemic, the patient care delivery paradigm rapidly shifted to remote technological solutions. Tele-health reduced the susceptibility of the disease as well as the risk of its spread. More health organizations adopted RPM to enable CD management in the absence of personal encounters. The potential of the SHM framework for RPM is undoubtedly increasing. The current studies [17,18,20-25] on SHM have either reviewed the applications of IoT and/or ML in the healthcare domain. Other studies [26-30] reviewed the SHM from the prospect of architecture, security, privacy and other network related issues. However, no study has analyzed the AI and ubiquitous computing advances in SHM frameworks for RPM. The key motivation of this comprehensive survey is to present the SHM architectures that target health data analysis using real-time monitoring of vital signs and patient context with state-of-the-art ML techniques. The major advantages, developments, distinctive architectural structure, components, technical challenges and possibilities in SHM are briefly discussed. A review of various recent cloud and fog computing based architectures, major ML implementation challenges, prospects and future trends is also presented. The survey primarily encourages the data driven predictive analytics aspects of healthcare and the development of ML models for

health empowerment.

1.4. Our contribution

Comprehensive reviews in this area are mandatory for new investigators as most surveys are providing an overview of the prevailing technological progress. Most review articles discuss the tools and technologies in various different aspects. This article discusses the most recent development in the SHM frameworks from 2016 to March 2021 in a realistic perspective. This comprehensive survey is to present the SHM architectures that target health data analysis using real-time monitoring of vital signs and patient context with state-of-the-art ML techniques.

- Analyzed AI and ubiquitous computing progress in the SHM framework for RPM.
- Classification of state-of-the-art surveys/review articles on the basis of various parameters is presented.
- Presented a comprehensive review of recent real-time SHM frameworks powered by AI, ML, cloud and edge computing, and analytics.
- Discusses the architecture, components, applications, intelligence involved, advances, challenges, issues and future path in the field of SHM.
- Key ML implementation challenges, prospects and future trends are also presented.
- An interesting taxonomy of research articles surveyed is presented on the basis of wellness, elderly health care and patient suffering from CD.

1.5. Outline

The rest of the paper is structured as per the outline: Section 2 presents the methodology for selecting suitable papers for this comprehensive survey. The development, distinctive architectural structure and components of SHM are briefly discussed in Section 3. The contributions of recently published review papers are also presented in Section 3. The technical challenges and prospects in the SHM framework are described in Section 4. Section 4 also provides a comprehensive review of the various architectures proposed in various research articles based on an interesting classification. Section 5 presents the key challenges of ML implementation in the SHM frameworks. In Section 6, an interesting assortment of reviews and research publications is offered. Section 7 concludes the review paper by providing a comprehensive discussion explaining the key benefits of SHM systems and future trends in the systems.

2. Methodology for review

The preferred reporting items for comprehensive review have been chosen using PRISMA, which is a systematic review methodology [31]. The PRISMA is a four-step selection process with identification, screening, eligibility, and inclusion.

2.1. Article search and selection strategy

For this review, the articles from scientific archives such as Elsevier, Springer, IEEE, Google Scholar and ACM covering years 2016 to March–2021 has been screened. The resources offered cover scientific and technical literature and offer a wealth of information about research efforts in a broad but relevant field. As mentioned in Table 1, this scope is covered by relevant and important keywords. Fig. 3 shows the actual query string at the top. Table 1 displays the keywords used to find eligible articles, as well as the number of articles found. This study is limited to studies in English-language. Mostly, the articles published in journals have been included, as they are complete and appropriate scientific work according to this survey. We have also included other relevant articles to connect certain concepts and techniques. To identify

Table 1
Searched keywords and results.

SN.	Keywords			Total results
	All the words	With exact phrase	With at least one word	
1	Healthcare	“Remote Patient Monitoring” (RPM)	“Machine Learning” (ML), “Deep Learning” (DL), “Neural Network” (NN)	2540
2	“Smart healthcare”	RPM	“ML”, “DL”, “NN”	451
3	“Smart healthcare” “chronic disease”	RPM	“ML”, “DL”, “NN”, cloud, ubiquitous, pervasive	144
4	“Smart healthcare” “chronic disease”	RPM	“ML”, “DL”, “NN”, cloud, ubiquitous, pervasive, prediction	146

more related papers, references of the selected papers were also searched and referred.

2.2. Search results

Initially, by searching various literature sources, 2540 studies were identified. After that, three iterations of screening and filtering were carried out. Duplicate articles were removed after the first iteration, leaving only 451 articles published in the last five years (2016–March-2021) for screening. The papers are screened based on their titles and keywords, and those that were outside the scope of our domain were excluded. The abstracts of 146 publications were read in the second iteration to filter the results. Articles that aren't included are either out of our domain's scope or don't match our criteria. Thus, a total of 146 studies were accessed and included to be evaluated for eligibility. In the final iteration, after complete text reading and rejecting the papers outside the scope, 50 articles are selected for final review.

Fig. 3 depicts the flow of study selection process. Fig. 4 depicts the number of eligible articles found for this survey based on publication venue. The most common publication venue is Elsevier Journals (40.0 %). The second most common publication venue is Springer Journals (32.0 %). The remaining articles (28.0 %) belong to other reputed Journals.

3. Smart healthcare monitoring frameworks

3.1. Introduction

The feasibility of RPM with the SHM framework was somewhat questionable before the COVID-19 pandemic, now it is a proven commodity and is on its way to becoming ubiquitous. Also, the increasing rate of aging population and deaths due to CDs such as CVD, cancer, diabetes and respiratory disease pose many challenges in healthcare. Overall, CDs are responsible for more than 70 % of global deaths. SHM frameworks are rapidly establishing themselves as the most effective tools for CD management. The SHM frameworks/architectures are primarily focused on remote monitoring of elderly patients, patients with chronic diseases, and wellness conditions. The goal of these SHM frameworks is to provide valuable knowledge by reviewing the patient's vital signs, history and symptoms in real time to better healthcare for patients, reduce disease progression and discover the causes of diseases.

Despite excellent infrastructure and advanced technologies, traditional health services cannot meet the needs of the present and the future. Medical services are not affordable or accessible to everyone these days, but smart healthcare enables stakeholders to manage some of their emergencies. The SHM framework not only eliminates geographical barriers by monitoring patients remotely but also reduces patient

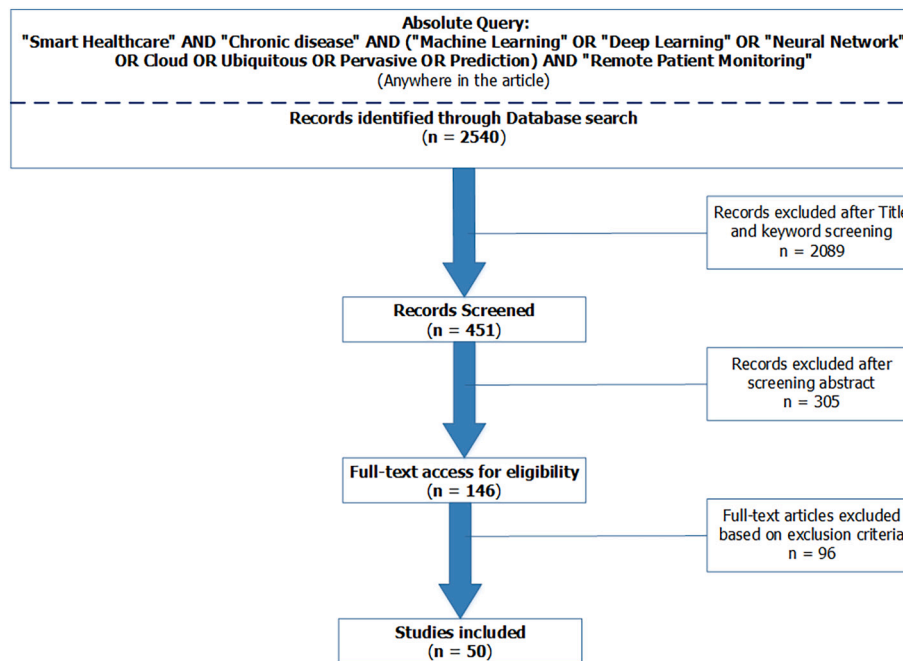


Fig. 3. Flow for study search and selection strategy based on the PRISMA.

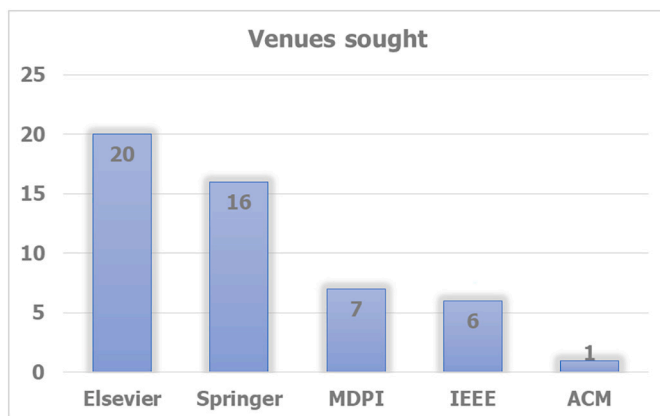


Fig. 4. Number of studies based on publication venue.

care costs. Thus, these frameworks provide many opportunities for patient monitoring at home and for identifying and preventing harmful diseases and conditions [32].

3.2. Evolution of SHM

Medical rehabilitation was introduced in the mid-20th century, which faced some obstacles, including long-term observation, supportive facilities, availability, and intensive treatment. One promising way to address the above problems is by adopting IoT and AI technologies and making medical service systems intelligent. IoT can improve the quality of rehabilitation systems. The authors [18] surveyed and discussed various IoT applications in healthcare. IoT was first proposed by Brock [33] and Ashton [34] who founded the Auto-ID Center at the “Massachusetts Institute of Technology” (MIT). A report on convergent technology [35] focused on integrating ‘Information and Communication Technology (ICT)’ with nanotechnology to improve the productivity of nations and the quality of life of people. In 2005, a report [36] suggested combining IoT with other technologies such as WSN, Object Identification and Embedded Systems, etc. to remotely tag, understand

and control objects on the Internet. In 2008, the term “smart planet” was coined by IBM Corp. In recent years, large IoT-based systems and applications have been developed for various domains such as healthcare and have become popular following new concepts such as smart cities. IoT allows for pervasive connectivity by allowing resources and devices on the network to receive real-time data and support ubiquitous decision-making activities. Public facilities and resources in many cities are now linked seamlessly to the wider interactions that exist between things, humans, or both. IoT and inter-linked technologies in smart cities have been able to improve healthcare infrastructure. In this context, a good classification of sensors for IoMT has been presented by Ray et al. [26] The authors [17,18] summarize IoT applications in healthcare and propose future research trends and directions in this area.

Sadoughi et al. [21] identified and studied existing medical IoT advances. The most up-to-date experimental and functional IoT knowledge in medicine and its intra-domains with bibliographic details of IoT research publications, has been provided.

Malasinghe et al. [37] investigated the latest developments in remote healthcare and monitoring, including both contact and non-contact technologies. The authors of the review outlined specific concerns that most SHM systems have.

The authors Al Hemairy et al. [38] first classified ‘healthcare monitoring systems’ (HMS) developed by various developers on the basis of various classification criteria such as mobility, security, context awareness etc. The authors also proposed an “Elderly Healthcare Monitoring” (EHM) system that combines a range of developing technologies, such as mobile technology, biosensors, and communications networks, to create efficient, scalable solutions.

In telemedicine applications, the study [39] presents a systematic and exhaustive review on the prioritization of patients with several CDs. The challenges and open issues, concerning ‘patient prioritization’ in telemedicine are presented. They determined the need for a new ‘multiple-criteria decision-making theory’ to address the domain’s current issues.

The survey was conducted by Dang et al. [40] to examine the new IoT components, applications, and industry dynamics in healthcare. Since 2015, the authors surveyed cloud computing based healthcare applications and development in IoT. They also analyzed how the promising technologies like CC, AI, “Ambient Assisted Living (AAL)”,

big data, WSN, and WBAN are being used in healthcare. They discovered how IoT and global e-health policies influence the long-term growth of IoT and CC in the healthcare industry.

The study [41] examined at new IoT communication principles and technological innovations that could be used in smart healthcare applications. The emphasis is on low-power wireless technologies to enable energy-efficient healthcare-IoT systems.

SHM frameworks enabled with IoT and inter-linked technologies are capable of collecting data in real time and performing analytics immediately to handle emergency situations in a timely and appropriate manner. The care provided by the SHM using vital signs, clinically relevant information and activity context is an important component of virtual care and treatment. IoT has been able to enhance various medical applications in RPMs, fitness programs, CDs, rehabilitation and elderly care [42]. The authors [43] have recently shown increased research addressing RPM using mobile, wearable and sensor technology. The

potential for SHM adaptation to improve chronic care and telehealth will continue to grow over the next five years and stakeholders expect the market to double in the same period. Emphasis should be laid on educating people about medical care and improving the quality and patient experience through these tools.

3.3. SHM architectures

These frameworks integrate smart devices and record the patient's vital information and activity context. These usually combine WSN, WBAN technologies with IoT, for enabling patient monitoring. Also, it integrates other technologies such as AI and ML for disease diagnosis, identification, and prediction of health status. In addition, the technologies like CC, edge/fog computing are of utmost importance as the variety, volume and velocity of data is growing. Thus it is helpful to track down a patient suffering from CD without frequent hospital visits and

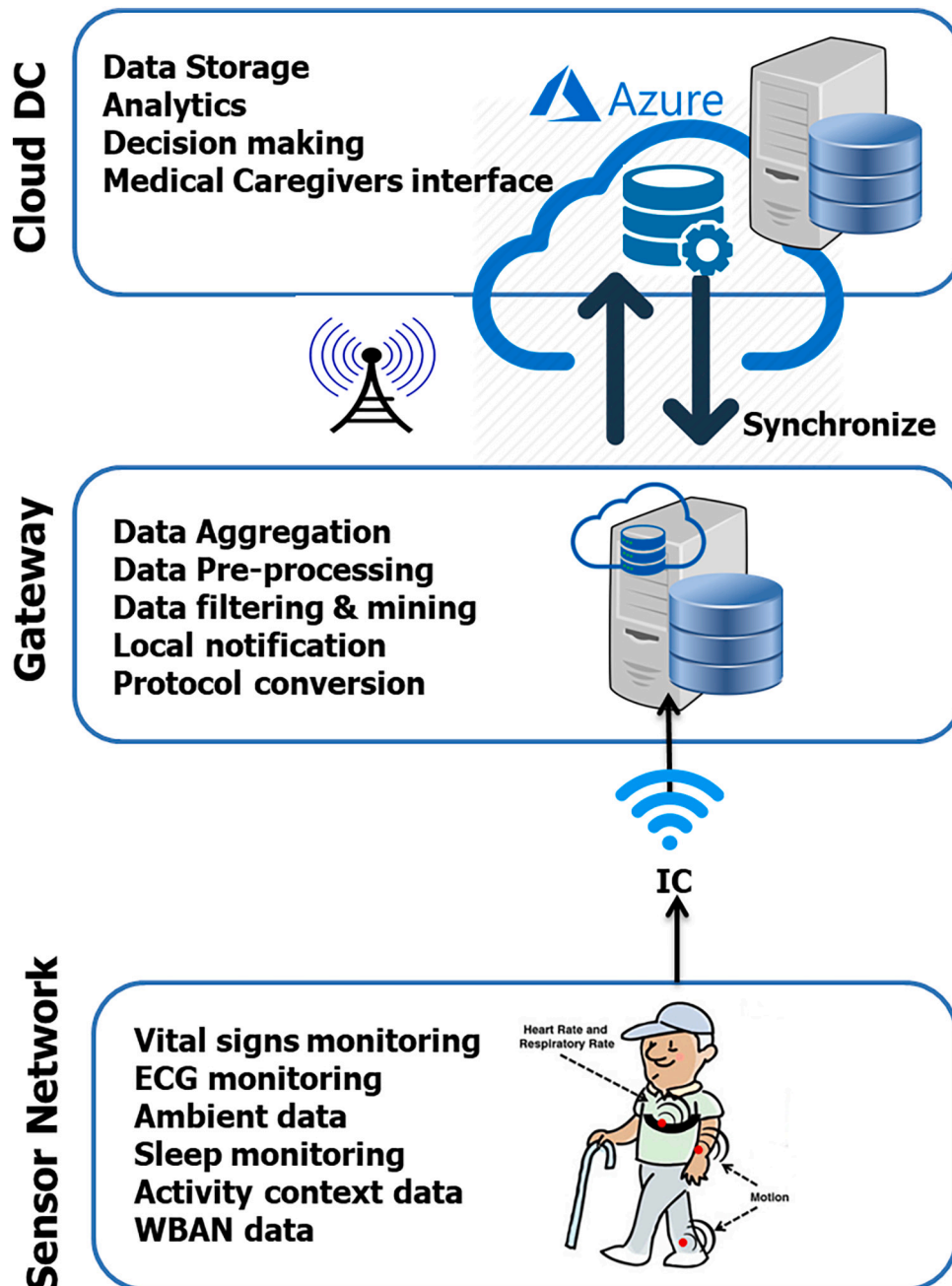


Fig. 5. Illustration of smart and ubiquitous healthcare monitoring framework.

examinations.

This comprehensive literature review will help to understand the architecture of the SHM framework and the applications of IoMT and/or ML in the healthcare sector. This systematic review also helps to understand the technical challenges and ML implementation challenges. The architectures are either based on cloud computing [44–51] or are of hybrid nature [52–65] which includes both fog and cloud computing. While some architecture involve only local computing [66,67], in another classification, architectures are based on 2, 3 or 4 tiers. The most common architectures are 3-tier [44,45,49–51,53–57,59,62–65,67] and 4-tier [46,52,58,60,61,66]. Only a few are 2-tier based [47,48,68].

Mardini et al. [69] surveyed recent applications in health monitoring and classified systems and their general architectures. The standards to be used and the challenges faced by the sector were discussed. Finally, the evaluation of these applications is presented and the potential future scope is discussed.

Albahari et al. [70] presented a comprehensive review of articles on priority-based sensor and triage techniques in telemedicine. The authors also examined articles describing the three-tier architecture of telemedicine. The challenges, benefits and recommendations are presented and some gaps are found. Finally, the issues related to its application and development and barriers to use are examined based on the findings presented in the literature.

Baig et al. [71] presented a review of 20 papers on Wearable Patient Monitoring (WPM) and investigated the issues of WPM solutions used by clinicians in patient care settings.

Ahmadi et al. [24] have conducted an extensive literature review of healthcare-IoT to determine the critical technologies, components, architecture, areas of application, security and interoperability issues and impacts.

An illustration of a typical architectural structure is presented in Fig. 5 that can form the basis for a good SHM framework. For clarification purposes, the typical framework is divided into 3 tiers: sensor network, gateway, and cloud Data Center (DC). A brief description of each tier is as follows:

- Tier-I of the architecture includes the sensor network of the IoMT and this layer may be called the “perception layer”, “sensing tier” or the “data accumulation layer”. Here, smart gateways (aka data aggregators) are responsible for the synchronization of the acquired data. The model [58,59] exploits ambient sensors and medical sensors at the acquisition layer to collect the patient data.
- Tier-II of the framework depicts data aggregation, cleaning and filtering functions. This layer can be deployed at the edge of the network (i.e. at Gateway) and used for feature selection and data analytics tasks. The computing operations done at the edge by bringing cloud services to the edge of the network is known as fog computing. The authors [16] examined a range edge computing architectures and techniques that are currently available and evolving.
- Tier-III comprises of cloud DCs and is also known as “Cloud Processing Layer”. Data processed from Tier-II (Fog/Edge Server), is transmitted to Cloud DC for mass storage and in-depth analysis. Cloud computing provides large-scale data storage, elastic computational resources and resource sharing for stakeholders. The main functions of this layer are: collecting and storing registered patient (user) information, analyzing, making decisions, and providing an application interface to caregivers and doctors. This tier is connected to multiple channels for notification purposes. The characteristics of cloud-based architecture, and the challenges of IoT in healthcare, are presented by Ahmadi et al. [24]. Darwish et al. [30], provided a detailed overview of the current literature on the use of CC and IoT in healthcare applications to solve different issues. A brief overview of the integration of CC and IoT paradigms as well as their application to health care is also presented.

3.4. Components of SHM architectures

5G mobile communication is expected to offer extended coverage, effective connection between IoT things/objects even in high mobility and interoperability of multiple wireless access technologies. The emergence of 5G communications technology led to the investigation of tactical Internet-based applications, particularly in the healthcare and robotics sectors [72]. In this section, the major components of SHM are listed and briefly defined. Fig. 6 shows the classification of major components. The first and primary component of this taxonomy is about the healthcare network. The network is made up of three major components: architecture, platform and topology, and it facilitates communication in healthcare.

Sensors, actuators and the Internet are crucial in the development of IoT solutions for the SHM framework. IoT can be termed as the connected components used on devices for health monitoring. The bottom layer of an IoT system includes sensor connectivity and a network for collecting data. This layer is an important aspect of the IoT system as it connects the gateway and the network layer through the Internet. Sensors are primarily used to collect vital signs, health data and data from the patient's surrounding environment. The data collection system facilitates the process of data collection, transfer to and from the communication devices within the network. End-to-end connected devices in the architecture are responsible for delivering patient data from home to the hospital and/or caregivers. The SHM framework harness the capabilities of stationary and mobile electronic devices, including laptops, smartphones, and medical terminals, and creates heterogeneous computing networks [73].

Many communication solutions, such as Bluetooth, WiFi, ZigBee, and GSM, allow the interconnection of devices using various access networks, including RFID, devices with wireless sensors [74–76], and any smart object connected to the Internet over a physical IP [77]. Wireless standards like as Lora, ZigBee, and Bluetooth are used by most healthcare systems to communicate data over local and global networks [78].

However, in patient care delivery environments these smart devices generate vast amounts of heterogeneous data, also known as big data, at high velocity. Advanced storage technologies such as “Hadoop Distributed File System” (HDFS) are a core phase of big data analysis. For more stakeholders to support ubiquitous healthcare IoT applications and adopt and scale data mining approaches on big data, migrating to cloud technologies becomes an urgent need.

Cloud and edge computing are essential for smart and efficient healthcare systems in smart cities [79]. CC provides rapid deployment, flexible resources, and economies of scale by distributing computing resources such as CPUs, networking, databases, software [11] and data analytics platforms over the Internet. Unlike the centralized paradigm CC, fog computing is a decentralized paradigm of computing. “Fog computing” (FC) was initially coined by industry [80].

Data analysis methods can be described as exploratory or confirmatory whereas statistical analysis and mathematical modeling are robust tools that allow a researcher to draw meaningful conclusions from the data. These tools and modalities enable clinicians and patients to help monitor, manage, and prevent CD and conditions. ML is primarily an exploratory and comprehensive AI technique used to build models that can learn from data. However, statistical methods are often incorporated directly into many ML algorithms. In the SHM framework, ML is used to build models that help predict risks and provide diagnosis and treatment based on medical data.

4. Technical challenges smart healthcare monitoring frameworks

Among the many developed technologies in the healthcare industry, SHM for RPM is one of the most influential. This technology is opening new avenues in existing healthcare services. As these tools continue to mature, researchers and developers are addressing significant

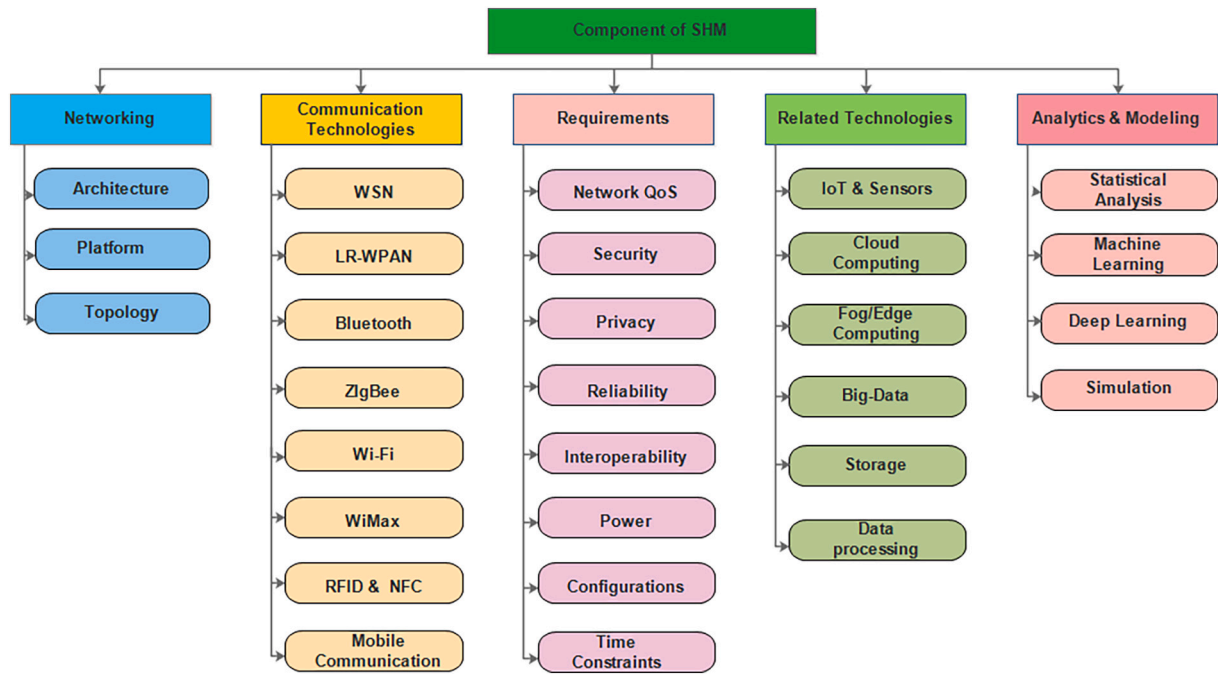


Fig. 6. Classification of major components of SHM.

challenges to increase their capabilities and effectiveness.

In this section we will discuss many of the technical challenges of existing legacy systems and the extent to which these challenges have been addressed. The challenges are divided into three categories as shown in Fig. 7.

4.1. Data and computational challenges

RPM is one of the major applications of AAL. AAL systems deployed in patient environments generate large amounts of data. Even routine monitoring of patients using AAL generates big data [16,81].

The 5Vs of Healthcare Big Data include: Velocity, Volume, Variety, Veracity or Value, and Validity. Due to new technological advancements the data is being generated at high velocity and the associated need for

processing and analysis of such huge volume of data is increasing. The challenge of storing and managing data from the SHM framework lies in the properties of big data. Meaningful health care data such as ECG data, clinical data and patient references such as activity data comes in a variety of formats and sizes, and the pursuit of knowledge organizes that the more types of information we integrate, the richer the insights. The challenge for SHM lies with the data diversity as well. Standardization and dissemination of all information in a common format will increase adoption of insights. Therefore, it is necessary to remove noisy, biased and incomplete data through pre-processing. In addition to veracity, the validity of the data is a significant challenge in SHM. Validity pertains to completeness, curation and real-time updates. To ensure valid data, it is essential that the information generated is accepted using scientific protocols and methods.

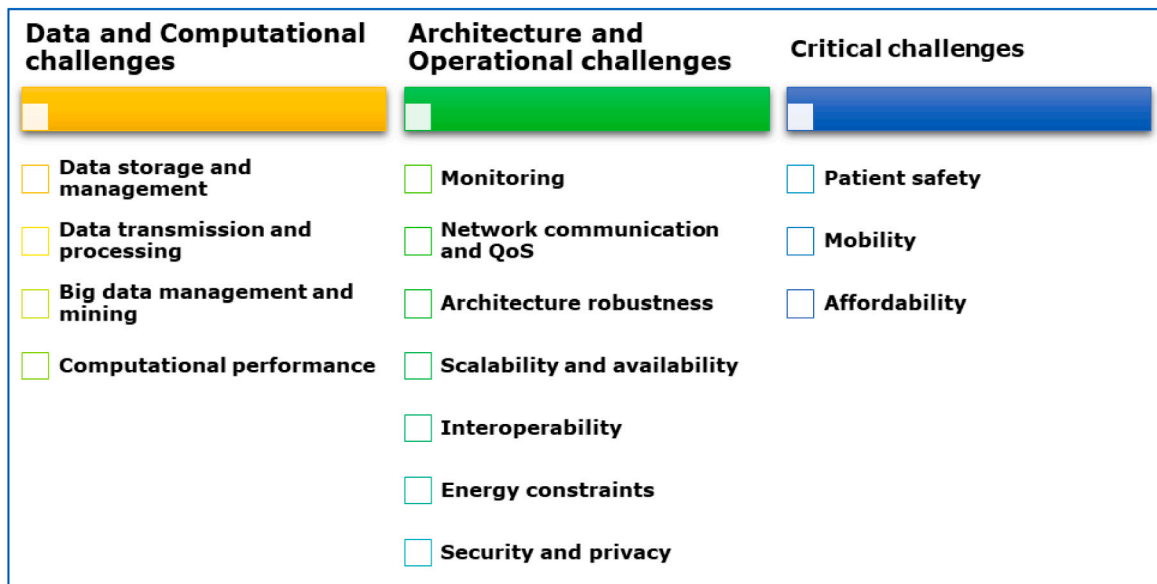


Fig. 7. Categorization of technical challenges in SHM frameworks.

Sakr and Elgammal [82] recognized and investigated a few of the significant difficulties in healthcare systems which have been successfully solved by recent breakthroughs in ICT. Considering the improvement and efficacy of health services quality, the authors focused on sensor technology, IoT, CC, and Big Data analytics systems.

From 2010 to 2019, the authors [4] gave a comprehensive picture of the IoT and related ML-based solutions that were built or employed. The techniques discussed here are intended for a variety of applications in healthcare, including tracking cardiac disorders, predicting heart attacks, detecting human behaviours, and classifying breast cancer.

Faust et al. [22] presented a review of DL algorithms for healthcare applications focused on physiological signals. The authors also stated DL performs better than typical data analysis and ML algorithms for big and varied datasets.

Purushotham et al. [23] used DL models to present bench-marking results for a variety of clinical prediction tasks, including length of stay prediction, mortality prediction, and ICD-9 code category prediction. According to their findings, the DL models greatly exceeded all other techniques, especially when the input medical data is 'raw' time-series data.

The research work [16] examined edge intelligence that uses state-of-the-art DL techniques to target health data classification and prediction, as well as the monitoring and recognition of vital signs. This study identifies potential research recommendations as well as the general use of IoT technologies for evolution of edge computing services in healthcare.

The health informatics sector is expected to benefit from the rapid development of big data analysis tools for the management of CD using clinical decision support, disease prediction and diagnosis. ML especially DL technology coupled with IoT based SHM framework promotes big data processing capabilities and proves to be extremely powerful. DL provides a subset of large deep computation models. But, it requires high processing capabilities to process such a huge amount of data and train the ML/DL model on top of it. Also, the exponential growth of health care data cannot be managed using traditional platforms and frameworks. Therefore, the use of cloud environments has led to a paradigm shift in the storage, management, analysis and application of ML for knowledge discovery in the healthcare sector. Advanced cloud platforms with integrated ML capabilities including Microsoft Azure, Apache Spark, Amazon SageMaker capable of handling big data give great hope for developing SHMs for innovative medical applications. Hadoop is a software framework that has proven successful in tackling most of the challenges discussed above for medical applications. Building smart RPM models using cloud-based technologies will preserve the lives of patients, especially the elderly who live alone.

4.2. Architecture and operational challenges

SHM implementations in smart city applications are taking full advantage of existing synergies. We have already discussed the general architecture as well as the various components of SHM. It is clear that this intense research involves a fusion of many fields.

SHM frameworks are designed to obtain a number of clinical data and context data from patients. The most common data is respiration rate, oxygen saturation, heartbeats, Electroencephalogram (EEG), Electrocardiogram (ECG), glucose level, blood pressure (BP), temperature and signals from the nervous system. Reference data is activity such as sleep, movement, activity level is usually collected. Various storage and computing technologies address the challenges of managing and processing big data arising from ubiquitous and SHM frameworks. However, the large number of stakeholders in the SHM framework ecosystem faces various challenges related to architecture and operation. In this section, we present the various architectural and operational challenges.

4.2.1. Disease monitoring

In disease monitoring, various sensors and devices with embedded sensors and wireless data transmission capability are involved. With the advancement of technology, sensors cannot be the only medical sensors; it can be a camera or a smartphone. The authors, Hernandez et al. [43] investigated that how wearable, mobile, and textile sensing technology has pervaded the healthcare industry by providing technological solutions to difficult problems including continuous monitoring at home and personalized medicines. It is not possible to have all such data acquisition devices as wearables. In this context, the authors [37] examined both contact and non-contact techniques and outlined specific concerns that most systems have. The authors [71] examined the constraints and challenges of WPM solutions adopted by clinicians in acute, community and care settings.

In addition to advances in sensor technology, many systems face the most common challenge of signal quality [83,84]. Also, the biosensors have specific requirements on body position and posture to provide accurate and reliable measurements. To solve the problem, authors [85] suggested textile integrated active sensors.

4.2.2. Network communication and QoS

In addition to providing appropriate health services for various human diseases, the SHM system aims to provide continuous real-time data for better disease management, timely treatment and minimization of errors. Real-time monitoring comes with the challenge of connectivity. The paper [86] has offered a broad analysis of current developments in three "RF-sensing" technologies for AAL in the field of healthcare. The article discussed the details concerning different sensors, deployment, configuration, and performance evaluation and presented some challenges that usually encounters while deployment and that need to be addressed. Continuous device connectivity with Bluetooth or Zigbee, WiFi or 3G/4G networks can cause these issues. Connectivity may cause delays in providing results and generating alerts due to data loss, buffering, network errors, monitoring or processing [87,88]. Such network communication and QoS issues can put the patient at risk. Various robust architectures have been developed to deal with such errors and risks. These architectures are multi-tiered [58] and/or cross-layered. Furthermore, various cloud-based as well as fog computing based architectures have recently been proposed for fault tolerance. The study [89] addresses the reliability concerns with existing healthcare on broadband communication infrastructure, and proposes a cloud-based mobile healthcare to improve QoS parameters such as delay and response time. Fog computing is therefore considered suitable for applications that require real-time, low latency, high scalability and high response times, especially in healthcare applications [90].

4.2.3. Architectural robustness

Traditional SHM systems are not capable of handling big data and cannot be relied upon to monitor patients suffering from serious health ailments. AI, on the other hand, helps stakeholders address three key challenges: patient health, cost and quality of health care [91]. However, there is a need for an effective infrastructure for data sharing between patients, hospitals, pharmacies, insurance companies and emergency units. Cloud-based implementation is generally considered the natural choice in such scenarios. Big-data and computational challenges are also dealt with by the scalable and elastic nature of cloud platforms. Furthermore, MapReduce based models provide higher scalability and better performance with parallel processing. In remote areas, low signal strength, low transmission speed and poor battery life can cause connectivity problems. The QoS issues can put the patients at risk. In this context, various edge-based architectures have been proposed in the literature to provide robustness. Edge devices are used at the local end to manage the risk of delayed alert generation due to network issues. These tools can run independently or in synchronization with cloud nodes and are also capable of running ML models to ascertain the health status of the patient. With 5G it is also possible to monitor

patients in real time with low latency 1–10 ms. This real-time experience will provide more information about the day-to-day health of the patients.

4.2.4. Scalability and availability

The challenge of scalability is associated with disaster situations such as the COVID-19 pandemic and an aging population where there is an increasing demand for health services. Widespread deployment of SHMs is not expected until around 2025, although the COVID-19 pandemic has probably accelerated this timeline significantly. Vendor hardware exclusivity, problems with stake-holder interfaces, inadequate features, usability, scalability, interoperability, compatibility, unreasonable costs, and ineffective validation are among the identified limitations [1]. Cloud and fog computing provides scalability and availability in case of emergencies, in addition to storage and cost-effectiveness. In addition, hardware failure and system upgrades can create an availability challenge that needs to be addressed using quality hardware and software technologies.

4.2.5. Interoperability

The complex and heterogeneous nature of IoMT based infrastructure makes interoperability difficult. IoMT systems are designed to be highly interoperable these days [45]. These systems are capable of seamlessly moving data from WBAN and AAL devices to cloud and edge gateways for processing and analysis. The challenge is significant due to the growing manufacturing market for these devices. Various manufacturers confirm complete interoperability using the tools they offer [92]. Addressing interoperability is sophisticated work and is based on the standardization community. However the increasing complexity is better dealt with by efficient and effective software design processes. In this context, Albahari et al. [20] presented a comprehensive study that reviewed all the major developments in the IoT-based telemedicine architecture. The authors presented a classification-based analysis of the literature on IoT-based telemedicine and a crossover with different disease groups.

4.2.6. Energy constraints

AAL devices and sensors must be active at all times for continuous monitoring and real-time feedback. Steady monitoring may be hindered by the limited battery power of these devices. Energy systems in a SHM environment are not directly connected to the patient. Therefore, batteries in medical devices and equipment need to meet very high standards to ensure efficiency, reliability and safety. SHM needs efficient power management system and it should be developed to reduce power consumption. The challenge must be well addressed by developing energy efficient devices and sensors, or by increasing the power of the batteries attached to the devices. In that context good suggestions are given by the authors [93] to improve the power of IoT devices.

4.2.7. Security and privacy

Security can be defined as managing the validity and setting certain access rules for patient programs and information. The SHM framework uses IoMT with various computing platforms and communication networks. The increasing use of mobile and wearable technologies in IoMT poses a serious security concern that is no longer scrupulously investigated. IoMT security is a significant challenge that is often addressed through weak or default protocols [94]. Also, stakeholders in healthcare are less aware of information security vulnerabilities and attacks. Medical data has become a popular target for ransomware and other attacks these days [94]. From a healthcare perspective, IoT privacy and security issues as well as potential threats, attack forms, and security configurations have been thoroughly investigated in [40]. The well-known existing security models have been analyzed to cope with security threats. Finally, the article highlighted opportunities, trends and challenges for the future development in healthcare-IoT.

‘Information Security’ provides for message integrity and data

confidentiality. Integrity here means maintaining and ensuring the completeness and accuracy of data throughout its lifecycle. On the other hand, confidentiality is a privacy component that enforces restricted access to protect data from unauthorized users.

Significant privacy and security issues, crowdsourcing for the rapid collection of large amounts of clinical data, open research barriers, and potential IoMT considerations have all been addressed by the authors [41]. The authors [95] proposed a privacy-preserving framework with a clustering-based distributed analysis approach for the analysis of bio-signal data. In our view, there are many aspects to a robust and effective cyber security and privacy strategy for modern health care networks. These aspects are 1. End-to-end security for software and devices; 2. Information Security and Confidentiality; 3. Strong encryption for data on the network; 4. Patient privacy regulation by government and policymakers.

4.3. Technical concerns and prospects in SHM

There are many challenges and opportunities involved in this technological ecosystem amid monitoring through SHM. Furthermore, the major concerns in the adoption of these structures are affordability, patient safety and mobility. Disease monitoring itself is becoming a challenge in the presence of other health challenges including CDs, aging population, cost of hospitalization and risk of medical errors. Medical errors can be encountered through the data and computational challenges, and architectural and operational challenges discussed above.

5G networks are capable of providing far better healthcare facilities including smart hospitals and assistive robotics. Further improvements in textile sensor design, signal quality and VLSI techniques are trying to meet these expectations. The technical constraints of IoT platforms (such as energy, processing and storage) are compensated by the cloud with their scalable nature. 5Vs of Healthcare Big Data are well addressed by cloud and edge based frameworks. Cloud platforms have now benefited from IoT and are expanding their scope to deal with things in the real world and provide many new services in a distributed and dynamic manner. The use of fog layer in the e-health care system improves the reliability and energy efficiency problems, and also supports the mobility of the user. The research article [96] discussed the emerging issues in M-Health, as well as research gaps, opportunities, and patterns.

The energy systems in SHM are hindering the patient's mobility. Several concerns related to patient efficiency, reliability and safety need to be addressed with energy efficient devices and sensors or by increasing the battery power attached to the devices.

Other technical challenges associated with surveillance that prevent clinical adoption of SHMs include reliability. 5G's technical specifications surpass other wireless protocols in terms of reducing latency, energy consumption, and improving reliability. In our view, there are many aspects to a robust and effective cyber security and privacy strategy for modern health care networks. There is a need for continuous and rigorous testing to identify safety deficiencies.

While many SHM systems have been designed and implemented with great potential benefits, some parts of it are still in their primary stages, and many open concerns and challenges need to be carefully examined. This article identifies the main challenges and emphasizes the value of SHM systems that take advantage of novel technologies including AI, DL, IoT, and Big Data to provide reliable, cost-conscious, and completely connected systems.

4.4. Comprehensive review of ubiquitous and SHM frameworks based on ML

Several IoT based cloud-centric frameworks for disease monitoring and diagnosis have been proposed in the literature. This work includes a survey of research articles related to the monitoring of: Elderly patients, wellness and chronic diseases. In Table 2 (see Fig. 8), an interesting

Table 2
A taxonomy of surveyed research articles based on various criteria.

Author/reference & YOP	Elderly and/or emergency healthcare	Chronic or other disease monitoring	Wellness/monitoring	Edge/fog/local computing	Cloud computing
[44,49,50]	✓	✓	✓		✓
[52,58–60,64,65]	✓	✓	✓	✓	✓
[45,46,51]			✓		✓
[68]		✓	✓		
[55]		✓		✓	✓
[66]	✓	✓	✓	✓	
[53,56,61–63]		✓	✓	✓	✓
[47]		✓			✓
[54,57]	✓	✓		✓	✓
[67]		✓		✓	
[48]	✓		✓		✓
This study	✓	✓	✓	✓	✓

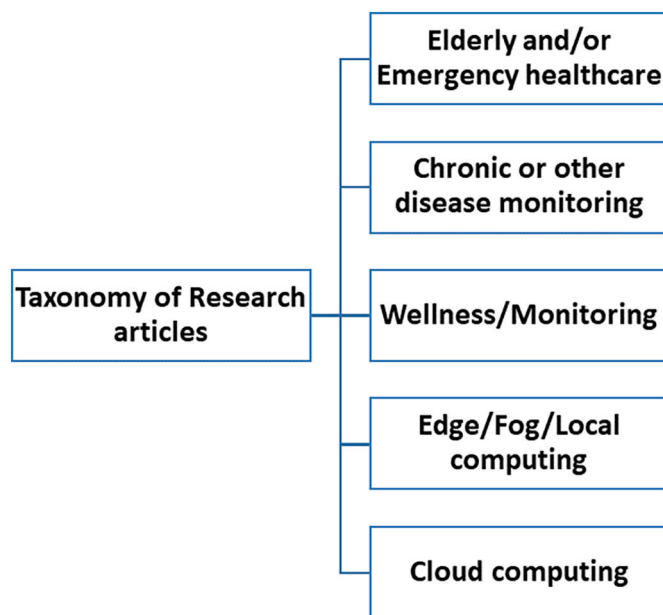


Fig. 8. Taxonomy of research articles surveyed.

taxonomy of research articles surveyed for this work has been presented. The symbol (✓) indicates that the research article employed the marked concept in their research. The previous research work on SHM systems is briefly discussed in the remainder of this section.

In this section, we present a chronological and architectural overview of the proposed SHM systems during 2016–2021 which is summarized in Table 4 from the ML perspective.

This intensive research involves fusion of several domains. To realize the scale of the issues and the recent approaches to face it, the review is primarily focuses on the ubiquitous, smart and remote HMS utilizing IoT and ML approaches. To show the rigorousness and range of research in this area only representative works published during 2016–2021 have been discussed. Of the 50 selected articles, 25 are research articles (50.0 %). The latter text of this section expresses the view of some recently published research articles.

Hassan et al. [44] proposed an intelligent hybrid model for remote monitoring of patient. The model is context-aware and adopts hybrid architecture with both cloud-based and local components. This model is used to monitor patients in the home environment, particularly the elderly suffering from chronic diseases (CDs). The model [44] predicts the patient's real-time health status by combining physiological signals, environmental conditions, and patient contexts. The model is designed for detecting emergencies for patients suffering from blood pressure

(BP) disorders and its effectiveness is validated through results of experiments. The major drawback of model is that it is downloading and copying the ML model from the cloud. The combination of tree based classifiers and sampling techniques used in the model performed well, but this model has its own drawbacks such as over-fitting.

The authors [52] proposed a context aware framework “Hybrid Real-time Remote Monitoring” (HRRM) for monitoring the patient remotely. The framework utilizes the edge computing for categorization of the patient's real health status at the local/patient side. To achieve higher accuracy and faster classification, the framework utilized the Naïve Bayes with Whale Optimization algorithm. This framework is working in both online and offline mode. A study on patients with chronic BP disorder has been done.

Syed et al. [45] proposed a SHM architecture for AAL which utilized the ML algorithms to monitor and analyze the physical activities of elderly people, and IoMT for decision making and recommendations. The data has been collected through various wearable sensors connected to various parts of the subject's body. The collected data transferred to the cloud and data analysis layer. Map-Reduce platform with Naïve Bayes has been utilized for experiencing body motion. With an aggregate accuracy of 97.1 %, the framework monitors and estimates 12 physical tasks.

Bhatia and Sood [46] proposed a framework based on Healthcare-IoT, to assist smart workouts. The framework analyzed current health status during workouts and forecasted potential health vulnerabilities using the ANN model. Framework employed numerous smart sensors to monitor 5 subjects. The system performed well in comparison to the well-known models.

Esposito et al. [66] offered a framework for rapid prototyping of individual health monitoring. The architecture has been deployed in Android-based mobile devices. The build mobile application has been employed in a case study of monitoring and managing cardiac arrhythmias.

Pham et al. [53] proposed a dynamic neural network (DeepCare) model for prediction and determining progression of disease in patients with chronic illness. The proposed model utilized LSTM with timed events during the course of illness for disease progression modeling, prediction and recommendation. The model demonstrated improved accuracy over diabetes and mental health data.

Moghadas et al. [54] proposed a system for monitoring and classifying the health of individuals with cardiac disease. The system combined an Arduino board with a sensor module to monitor cardiac rhythm and undertake electrocardiography. FC has been employed for diagnostic information rather than cloud computing to optimize data transmission delays. Finally, the k-Nearest Neighbor (k-NN) data mining algorithm has been used to classify and validate the type of cardiac arrhythmia.

Chatrati et al. [67] proposed a ‘smart home health monitoring

system' that alerts the caregiver after detecting any abnormality while analyzing the patient's BP and glucose levels at home. Hypertension and diabetes status are predicted with the help of conditional decision-making and ML approaches, respectively. The primary objective is to determine the status of high-BP and diabetes using a supervised ML classification algorithm by monitoring and analyzing the patient's glucose and BP readings. The SVM was found to be most suitable and accurate in the system.

In [55] an intelligent system is proposed for early identification and control the 'mosquito-borne' diseases. WBAN and IoT sensors were used to collect the necessary data, which included symptoms. Further the FC has been utilized for analyzing, categorizing and sharing the medical information between user and healthcare service. To segregate diverse mosquito-borne diseases and categorize individuals into the uninfected and infected classes, the suggested system used similarity coefficients and fuzzy k-NNs respectively. Further, the outbreak of mosquito-borne diseases has been represented and the chances of the user to acquire or spread the disease have been measured by PDO ('Probability of Disease Outbreak').

For ECG monitoring, S. Krishnan et al. [47] presented an IoT cloud architecture. The architecture is two tier with client and cloud tier. The article suggested the Elman Neural Network (ENN) classifier for data protection which forms cryptography and authentication while transferring medical data over cloud is suggested in this work. The model classifies the data as abnormal or normal. The work has been validated with OCSVM.

To foresee the possible disease along with the severity level, Verma and Sood [56] have proposed a 'Cloud-centric IoT based M-healthcare' framework. For application scenario, the authors designed the prototype for monitoring and diagnosing student healthcare and tested using the datasets of infectious diseases and heart disease. The diagnosis is done with well-known classification algorithms: SVM, k-NN, DT and Naïve Bayes (NB), and comparison results has been shown for different diseases.

Rahmani, et al. [57], in their research presented a Fog-assisted system architecture with 'Smart e-Health Gateway' at the edge of the network. Numerous characteristics of the gateway include local storage and data processing in real-time, and embedded data mining, among others. Many growing concerns in ubiquitous healthcare systems, including as scalability, energy efficiency, mobility, and robustness, can be addressed using this architecture. Lastly, the IoT-based 'Early Warning Score' (EWS) and some other features are described with help of a prototype in this article.

In a very interesting work, Motwani et al. [58] first presented a broad survey of ubiquitous, smart and networked healthcare systems for monitoring the health of elderly patients suffering from CDs in real time. Ahead in the article, the authors proposed "Smart Patient Monitoring and Recommendation" (SPMR) framework for classification and prediction of the real-time health status of patients with CDs. The model is based on cloud analytics and 'DL with novel loss optimization'. The framework is robust enough to work in both online and offline mode with recommendation facility. The framework has been tested with AAL, vitals and symptom data of patients with BP disorder. The higher value of accuracy and F-score has been achieved even for most imbalanced data by the employed DL model.

In another work [59], the authors proposed a three-tier Smart predictive healthcare framework for elderly patients who are under observation at home and suffering from CDs. The model exploits ambient sensors and medical sensors at the acquisition layer to collect the patient data. The novel DL algorithm at second layer has been used to achieve highly accurate classification of emergency cases in real time. The AAL framework has been tested with imbalanced, context aware, multi-class big data obtained through monitoring of blood pressure disorders.

For monitoring older patients with chronic conditions, the authors [60] proposed a hybrid AAL framework using the Nave Bayes-firefly

algorithm. This architecture takes advantage of IoT advancements to collect data from elderly patients and context situations to anticipate the patient's health status in real time. In essence, the authors suggested a classification framework for classifying a patient's health condition based on the minimum features that provide the maximum accuracy.

Bhatia and Sood [61] proposed a Fog-Cloud architecture, based on IoT, to observe and examine several health attributes of a person during the office hours. The authors defined a probabilistic measure to estimate the adversarial effects of various activities on personal health.

Sahil and Sood [62] proposed a 'Fog-Cloud centric IoT-based cyber physical framework' that provide medical support and helps in the evacuation of the panicked stranded persons from catastrophic environment. The proposed framework's fog layer classifies stranded persons' 'panic health status' (PHS) in real time. After diagnosing PHS, to track the panic health susceptibility of the trapped panicked persons the system utilizes Bayesian Belief Network (BBN) at the cloud layer.

In a broader work [63] a new tri-fog health architecture has been proposed for physiological factor detection and resolving overloading in fog environment. In this 3 – tier architecture, layer 1 with "Rapid Kernel-PCA" is responsible for detecting the fault in data that is captured through the patient's WBAN; Layer 2 is responsible for predicting health status timely using "Two-level health hidden Markov model" (2 L-2HMM) by the help of temporal variations in data; Finally, layer 3 (Fog layer) detects the patient's health status using hybrid ML model SpikQ-Net. The model architecture utilizes biomedical, environment and context data for operation. Also, for timely service and lower response time a multi-objective spotted hyena optimization (MoSHO) algorithm has also been used. This work also shown a comparative analysis with prior HMS.

Tao et al. [68] proposed an RPM using RFID for early identification of suicidal and self-harm behaviour within a hospital based psychiatric facility. The model in RPM analyzes the patient's vital-signs and subtle motions in hospital. An ensemble model based on ML algorithms such as LR, DT, XGBoost, and Random Forest to determine the optimum position of RFID readers has been proposed.

Jung [48] proposed a hybrid awareness model for personalized elderly healthcare service for classifying the health status into positive or negative in a smart home environment. The model also proposed a hybrid inspection service middleware for the safety of elderly that classifies the status into safe and emergency. Based on activities and location of elderly patients, the middleware service assesses the health risk. The model acquires the vital and context data with wearable and motion sensors then analyzes with various ML algorithms.

The authors [64] proposed a three tier architecture for RPM based on smart home. The architecture utilized techniques like disseminated storage, mining and warning service along with the concept of fog as smart gateway. The patient's data has been processed at the fog layer in real-time. The notion of temporal mining, which involves calculating the patient's "temporal health index" (THI), was utilized to assess the complexity of the events.

In an interesting article, the authors Chen et al. [49] recognizes the importance of important physiological indicators such as physical exercise data and dietary information are extremely important in effective prevention of diabetes and post-hospitalization treatment. So, for better care and treatment of diabetes, they proposed a "5G-Smart Diabetes" system with personalized data analytics. The system has been tested with SVM, ANN and DT. Further the social networking service (SNS) in the system is facilitating the care and treatment for diabetic patients in a better way.

Abawajy and Hassan [50] presented a pervasive patient health monitoring (PPHM) system architecture with IoT and CC technologies. The use of ECG for real-time monitoring of patients with congestive heart failure has been demonstrated. The system is evaluated for QoS parameters such as scalability, flexibility and energy efficiency. The framework also utilizes the classification and clustering techniques to enable patient care. Through this article, the authors tried to address the

answer that how the patient can be remotely monitored and his health status can be evaluated.

The authors [65] proposed a hierarchical computing architecture (HiCH), utilizing fog as well as cloud. It uses ML-based intelligence and a ‘closed-loop management’ methodology at the network’s edge to make autonomous system adjustments based on the patient’s state. A case study concentrating on arrhythmia identification in patients with CVDs confirmed the model’s efficacy. The work performed classification of normal and abnormal ECG cycles. To manage the system resources, the work has extended the map IBM’s MAPE-K model.

4.5. SHM framework challenges: comparison

SHM frameworks are designed to obtain patients’ clinical and context data. The most critical data are respiration rate, oxygen saturation, heartbeats, EEG, ECG, glucose level, BP, temperature and signals from the nervous system. Also, Real-time monitoring comes with the challenge of connectivity. At the same time, continuous device connectivity with networks can cause QoS issues also. Connectivity may cause delays in providing results and generating alerts due to data loss, buffering, network errors, monitoring or processing. Low signal strength, low transmission speed and poor battery life can cause connectivity problems in remote areas. The network communication also suffers from QoS issues and can put the patient at risk.

Therefore, there is a need for fault-tolerant, robust, multi-tiered architecture with edge/fog computing to deal with the risks associated with connectivity and QoS. Thus the, frameworks: [44–47,49–51,56,60] are the most challenging, while frameworks: [48,52–55,57–59,61–68] are comparatively more robust and less challenging.

The common challenge is to manage and process big data arising from the ubiquitous SHM framework that can be tackled by efficient computing with cloud and edge computing.

5. ML implementation challenges in smart healthcare monitoring frameworks

The SHM framework enables patient emergency monitoring and diagnosis through advances in big data, sensor technologies and AI/ML. There is growing expectation that ML and DL models will help improve diagnostic procedures. However, there are many implementation challenges associated with the collection and processing of massive amounts of data to understand patients’ problems and then diagnose them through sophisticated AI and ML algorithms. In this section we discuss the ML implementation challenges in the SHM framework. Some of the major implementation challenges are represented in Fig. 9.

5.1. ML implementation challenges

5.1.1. Data preparation for ML algorithms

Depending on the specific health issue, images, medical IoT, EHR, genomic data and central medical repositories are the primary data sources for the ML model. Medical data collected through various sources is often in a non-structured, structured and semi-structured format and is incapable of producing knowledge through ML models, whereas pre-processing techniques result in accurate data for ML methods. Data pre-processing methods are mainly divided into the following four categories: 1) Integration of data obtained through different sources. 2) Data cleaning by handling outliers, noisy, missing and inconsistent data. 3) Data transformation for ML algorithms by consolidating the data into a single standard format. 4) Data reduction by dimensionality reduction and sampling.

Data preprocessing can also be employed for the purpose of reducing storage requirements and maintaining mining quality [97]. The authors [97] applied 3 instance selection algorithms for data preprocessing including genetic algorithms and evaluated using ML models: CART decision trees, K-NN, and SVM. Irrelevant or redundant features in

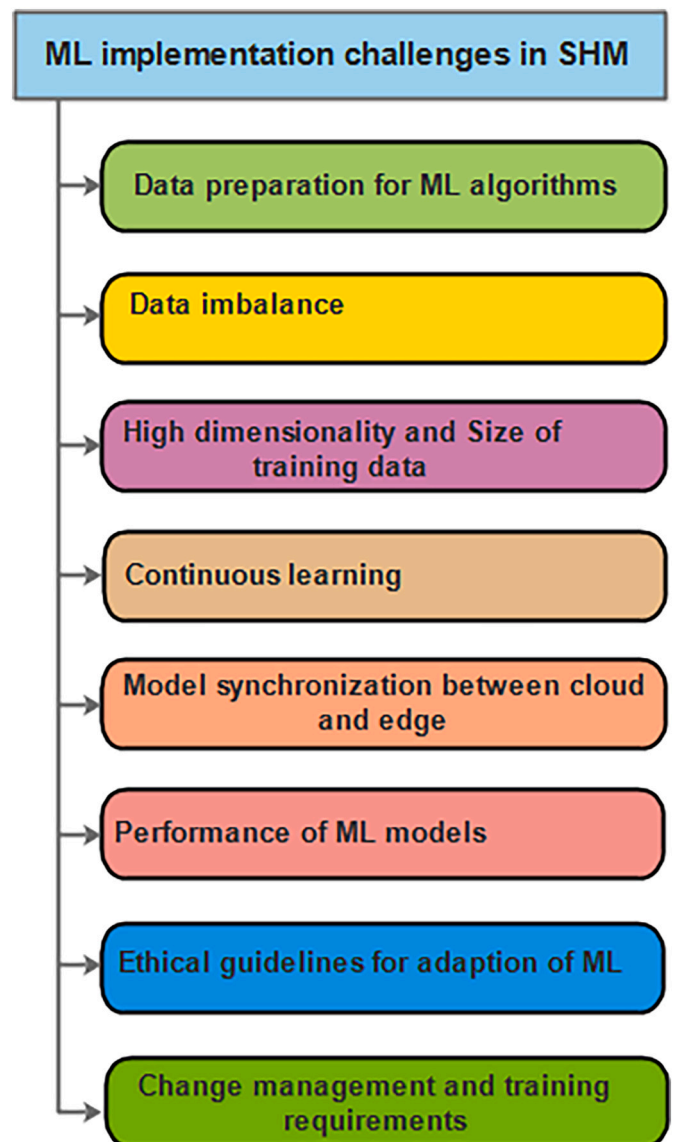


Fig. 9. ML implementation challenges in SHM frameworks.

health care data seriously affect subsequent model training and classification accuracy. However choosing relevant or removing irrelevant features greatly improves the performance of ML models. In this context, Zhang and Cao [98] proposed a filter feature selection based on relevance and mutual information, and evaluated based on 3 classifiers. Thus performance of state-of-the-art models depends on data modalities and data curation and preparation is a challenge.

5.1.2. Data imbalance

A data set is said to be class-imbalanced if the number of record-tuples for one class is significantly greater than the number of record-tuples for the other. In the above definition the former shall be called the majority class and the latter shall be called the minority class. As studied, most of the classifiers used in the SHM framework are performance driven which is based on overall accuracy and minimization of overall error. ML models assume a normal distribution of classes and received errors, so they are biased toward the majority classes rather than the minority. Thus it is misleading to consider accuracy to prove model efficiency. A small number of records—tuples in medical datasets represent a patient’s emergency state and a focus on overall accuracy can generate false-alarms. Class imbalance can be handled using kernel and

cost based methods and sampling. To deal with class imbalance, the authors [52] used sampling methods to process data chunks on Hadoop clusters. Rule based and tree based classifiers are used along with SMOTE and CB sampling to determine the status of patients suffering from BP disorder. In another work the authors [58,59] proposed a novel categorical cross entropy (CCE) loss optimization to deal with class imbalance. The authors used DL with CCE optimization to determine the health status patient with BP disorder. The framework harnesses the power of the cloud to store, process, and train classifiers on large imbalanced datasets. The effectiveness of the model in the presence of data imbalance can be proved with class wise F1-scores.

5.1.3. High dimensionality and size of training data

Medical data obtained through various sources like gene data, data collected through sensors eventually results in higher dimensions. However, many features in high dimensional data are not relevant to effectively detect patient status. In such a case, dimension reduction helps to improve the overall performance of ML and DL algorithms. The authors [99], used feature selection ('Fuzzy Backward Feature Elimination' - FBFE) and extraction ('Independent Component Analysis' - ICA) techniques to improve ML performance on cancer datasets. In another work the authors [100] used RFE to identify the minimum number of optimal features to effectively predict CKD. The authors [60] used fire-fly optimization to select minimum features and improve ML performance in SHM framework.

The size of medical data which is often viewed as big data is a challenge for training an ML model. Adequate data is needed to develop a performing ML model and to evaluate the model with high confidence. For example image analysis using DL algorithm requires large amount of valid data and its availability is a challenge [101]. Furthermore, any increase in the training data will increase the complexity and memory requirements of the model. On the other hand, DL models require more training data. DL algorithms for medical imaging have a high dependence on the quality and quantity of the training set [102]. Thus, improving the quality of the training dataset and the application of feature engineering certainly improves accuracy and patient-centeredness.

5.1.4. Continuous learning

Capturing a patient's vital signs and behavioral data through multiple sensors, social interaction and communication requires real-time data handling and learning. Continuous learning in healthcare brings with it a new set of opportunities and challenges. Continuous learning, or online ML, is a fundamental idea in which models continually learn and develop based on the input of ever-increasing amounts of data, while retaining previously learned knowledge [103,104]. The authors [105] discuss the main concepts and requirements for implementing continuous AI in radiology and illustrate them with examples of emerging applications. In healthcare, a pre-trained ML model will ideally assist the clinician in making diagnosis or management decisions. This will certainly pose a challenge to any new patient with unexpected symptoms.

New patient data and results from previous actions (actual diagnosis or treatment results) will be introduced into the pre-trained model for continual improvement. The model then transfers its previous knowledge to new data, hyper-tune its current result, or even takes on new functions. Although continuous ML systems seem ideal for medical reasons in practice, several challenges exist in implementing them. One of the main constraints of continuous ML models is catastrophic forgetfulness [106] (or an overwriting of previous knowledge) which can lead to a sudden decrease in performance with previously learned cases.

5.1.5. Model synchronization between cloud and edge

In SHM system the data is collected through sensors and AAL system which is transmitted to a centralized database using wireless

technology. However, due to the heterogeneity of each sensor's internal clock structure, the acquired data values are not synchronized for efficient evaluation. Hence, it becomes imperative to synchronize the data using smart gateways on temporal basis. The synchronized data is then transmitted over the network and stored in a cloud database and/or edge device. Here it is used for model training and prediction after pre-processing. If the SHM Framework does not have an edge device, the model is built on the cloud. This model sends updates, alerts and recommendations to the patient or caregiver's device. Non-availability of network and cloud service can pose a challenge and put the life of the patient at risk. Therefore, arrangements have been made to load/synchronize the model data on the local device/server. Hassan et al. [44] proposed a hybrid model where the major drawback of the model is that it is downloading and copying the ML model from the cloud to use on a local device. In contrast, the authors [58] applied an effective DL model for efficient classification of patient health, both at the cloud and locally, when dealing with heavily imbalanced data. It is still challenging to store, process, train and predict through ML on edge devices. This is a significant challenge for SHM frameworks with limited capabilities to drive modern data mining and ML techniques such as deep learning on big data.

5.1.6. Performance of ML models

ML ultimately improves patient care by enabling better diagnosis, repairation and clinical decisions [101]. However, developing and validating efficient models is a global challenge. The performance of state-of-the-art models depends on data modalities and low performance is a challenge. For example CNNs are suitable for images and RNNs are suitable for waveform analysis. The data in SHM is collected through various sources and application of a particular model may lead to poor performance of the model. In addition, there are many factors that affect the performance of ML models, including data curation, outliers, imbalance, training and validation sets, and performance parameters. The flip side of improved performance is the number of dimensions and attributes in the data. A larger number of features can lead to better predictive performance, but these models usually require more mathematical operations, and thus a longer model convergence time. However reducing the dimension or choosing relevant features can improve the performance and convergence time of the model. On the other hand, selection of a suitable validation set determined from clinical trials can be helpful for model validation. In order to evaluate ML models for health care, assessment metrics need to be tailored to those in the community concerned. The performance of ML models should be compared to baseline.

5.1.7. Ethical guidelines for adaption of ML

Any raw medical data is insufficient to make the right decisions. At each stage of model building, the involvement of a medical professional is critical to understand the characterization of the medical data [107]. There are many ethical and legal issues regarding the use of ML in healthcare. It is often difficult to logically explain the results of DL techniques [108]. In other words, every data feature, intermediate and final results must be confirmed by involving a medical professional. Ethical and legal issues related to the use of ML in health care should be handled by creating a better understanding of the data collected, processed and used in model building. Therefore, data exploration that involves statistical visualization of the data is also important for better understanding. Even though AI-powered systems have been shown to outperform humans in some analytical tasks, the lack of interpretability continues to be criticized. Nevertheless, interpretability is not a purely technical issue, instead it invites a host of medical, legal, ethical and social questions that require in-depth exploration.

5.1.8. Change management and training requirements

Change management is defined as the process of continuously renewing the infrastructure, and capabilities of healthcare facilities, to

meet the ever-changing needs of patients. However in the healthcare context, once the ML model is implemented, a major issue is whether it will continue to apply the same prediction logic as it was originally intended [109]. Following the worldwide adoption of such systems, interpretability of intelligent systems has become a necessity to explain and justify the decisions made by these systems, especially in the health sector [110]. Also, the quality of interpretable ML techniques for various health care applications depends on the training and validation of models [111]. In this regard, reinforcement learning (RL) has attracted significant attention in the medical community because of its potential to support the development of personalized treatments in line with the more general precision medicine vision [91]. The authors [6] have considered common heuristic approaches such as weighted early warning scoring systems and analyzed the possibility of employing intelligent algorithms.

5.2. ML concerns and prospects in SHM frameworks

There are many challenges and opportunities involved in the use of ML in the technological ecosystem amid monitoring through SHM. Data preparation, imbalance, size, dimension are posing new challenges. All of these pose a significant challenge to modern data mining and ML techniques, such as deep learning. For example, medical imaging today is largely manual because it requires a health professional to examine images to determine abnormalities [112]. However, DL algorithms can be used to automate this process and enhance the accuracy of the imaging process. The authors [25] highlighted the progress of the six DL techniques: Auto-encoder, RBM, DBN, RNN, CNN, and GAN with case studies. The paper explored some of the most basic and contemporary applications, and issues of DL approaches in the medical healthcare system.

Preparing data before they are fed into a ML algorithm remains a challenging task. Additionally, it is difficult to incorporate patient-specific factors in ML models. Data aggregators can be deployed at the edge of the network for this task.

The size of medical data which is often viewed as big data is a challenge for training an ML model. Big data and computational challenges are tackled with the help of scalable and elastic cloud computing platforms. Furthermore, MapReduce based models provide higher scalability and better performance with parallel processing. The Map-Reduce platform with Naïve Bayes has been used to classify body movements or bodily functions in [45].

Dimensionality is also a challenge that can affect model convergence and inference time. The dimensions can be reduced with some statistical and optimization techniques to improve the overall accuracy of the model. But due to data imbalance (aka bias-variance tradeoff) most ML models can be biased to majority class and hence generate wrong prediction and low performance. This trade-off can be optimized by carefully selecting the model architecture, training and validation process.

Under-fitting typically occurs when a model with a low capacity relative to the complexity of the problem and the dataset size is used. Under-fitting can be controlled by using a more parameter-rich model or weak regularization during training. Overfitting signifies surprisingly low performance on the validation set compared to the training set. Overfitting is usually prevented by cross validation and the use of multiple regularization techniques.

Furthermore, continuous learning, model synchronization, performance and interpretability ultimately lead to further challenges in SHM development for clinical implementation. Here is a need to develop ML algorithms capable for continual learning from clinical data [113]. Although continuous ML systems seem ideal for medical reasons in practice, several challenges exist in implementing them. Although continuous ML systems seem ideal for medical reasons in practice, several challenges in implementing them such as catastrophic oblivion exist. Thus human brain-like dynamics can improve the reliability of continuous learning.

To solve the problem of ML model synchronization, various Fog-Computing based models [54,55,57,63,64] have been proposed for storage, analysis, classification, diagnosis, medical information sharing, and optimization of data transmission delays.

The performance of predictive models can be improved by addressing various concerns with the help of efficient implementation of various good practices in ML knowledge. Although complex ML models such as CNNs are generally outperforming traditional and simple explanatory models, in the health care field, clinicians find it difficult to understand and rely on these complex models due to the lack of understanding and interpretation of their predictions. Nevertheless, interpretability is not a purely technical issue, instead it invites a host of medical, legal, ethical and social questions that require in-depth exploration [114]. In that context, open and interpretable AI [115] aims to determine the rationale for machine-made decisions, introduce trust, and reduce bias to improve human understanding. Open and Interpretable AI will certainly enhance the service delivery experience, traceability and confidence in the use of AI and ML tools in healthcare by addressing various challenges and issues. Therefore, interpretability and explanatory techniques for ML models in the SHM framework are an area of research.

5.3. Comprehensive review of ubiquitous and SHM frameworks: ML perspective

In this section, we present a chronological and architectural overview of the proposed SHM systems during 2016–2021 which is summarized in Table 4 from the ML perspective. The following attributes have been presented for each system: architecture type, usage of local and remote (edge and cloud intelligence), the application domain of the system, ML Method or algorithm used/proposed, the dataset utilized with features, and metrics based outcomes.

6. Lessons learned and future research directions

There are various diverse surveys of SHM are presented in the literature. The key objective of survey and review articles on SHM is to examine the systems in a specific context such as Architecture, applications, disease, issues and challenges. Those reviews targets SHM systems in a specific context. This survey looks at the field from a different standpoint, where all of these technologies are being used for RPM, to demonstrate the need for future study in the field. Here in this section, we have conferred the themes of existing surveys conducted earlier and have laid the basis for conducting the comprehensive review for this research work. This review proposes insights in order to offer valuable knowledge in this field of study. Of the 50 selected articles, 25 are review and survey articles (50.0 %).

This paper presented a comprehensive and systematic review based on PRISMA. The SHM papers which focus on ML are selected since the year 2016 to March-2021. In this survey, 50 articles out of the 146 articles are analyzed for comprehensive review. From this, 40 % of articles are selected from Elsevier, 32 % of articles are selected from Springer, 14 % of articles are selected from MDPI, 12 % articles are selected from the IEEE journals, and 1 article from is chosen from ACM journal. The most standard publishing sites are Elsevier Journals (40.0 %), Springer Journals (32.0 %) and other prestigious journals (28.0 %). Finally, the highest number of articles is taken from the Elsevier journals.

As studied that most of the articles either includes discussion or survey on architecture, application, intelligence involved, advances, challenges, issues and future path or mix of few of these topics. However, this research involves all of the topics mentioned above. In Table 3, a taxonomy of state-of-art surveys/review articles based on various criteria is presented. The symbol (✓) indicates that the article surveyed the checked topic. Table 3 attempts to convey the perception of some of the recently published review articles.

In a surge of COVID-19, SHM systems have become an exigent need. An AutoTriage strategy based on real-time DL approaches deployed at

Table 3
Taxonomy of state-of-art surveys/review articles based on various criteria.

Author/reference & YOP	Architecture	Applications	Integrated ML/DL	Advances	Challenges	Issues	Future path
[37]				✓		✓	
[70]		✓					
[24]	✓	✓			✓	✓	✓
[69]	✓	✓			✓		
[43]							
[71]					✓		
[25]							
[38]							
[30]		✓			✓	✓	
[39]		✓			✓	✓	
[17]		✓			✓		
[18]							
[82]					✓		
[20]	✓			✓			
[21]							
[22]			✓				
[23]							
[1]			✓				
[96]					✓		
[4]			✓				
[16]	✓		✓				
[86]				✓	✓		
[40]		✓			✓	✓	
[116]					✓		
[41]		✓			✓		
This Study	✓	✓	✓	✓	✓	✓	✓

the edge layer was proposed in a study [117]. An infrared camera was utilized to assess temperature, and DL was used to detect the forehead area. The multimodal DL system [118,119] has been proposed that employs smartphone sensors for determining the location of user and providing warning about risk-prone zones.

The SHM systems involve IoT networks generating massive amount of data every moment, which is being need to be processed. Wearable, wireless and ambient IoT sensors are continuously tracking a patient's vital signs and other contexts like sleep, exercise, and room temperature, etc. Hence, intensive processing capabilities are required for the huge amount of data. Thus, a business intelligence and analytics platform have been needed to gather, manage and analyze the complex big data generated through these devices. The integrated Machine and DL techniques with these architectures boost their performance and processing ability. The innovative DL models are particularly dominant for analyzing and diagnosing such a huge medical data.

Several analysis and diagnostic methods have been proposed in the research works for real-time RPM frameworks [120], although the requirement for QoS has not been appropriately dealt.

Like IoT, the CC is not new paradigm that offers virtually accessible unlimited storage and computing potential at a very low cost enabling effective analytics. Since, vast cloud DCs are spread across the globe, edge intelligence is also necessary to gain more information at the edge node in real-time. Edge intelligence attempts to combine AI and cognitive techniques for efficient processing of data.

Mobility is a necessity nowadays and connectivity is ubiquitous as both mobile and wearable devices become increasingly common, safe and popular among staff members and patients, thus opening up new avenues for user involvement and empowerment.

In this study, we have reviewed several ubiquitous and SHM frameworks that are using either cloud, fog or edge computing or combinations. The studies discussed here involve several AI, ML and DL techniques for chronic illness and health diagnosis. Although, the articles studied are based on wellness, elderly healthcare and patient suffering from CDs. In majority of the research works, the primary analysis and processing operations have been performed on the cloud layer. Despite the fact that Fog/Edge devices have constrained power, capacity, and resources, several recent research studies have begun to merge the Cloud, Fog, and Edge layers in order to improve overall

performance in terms of disease detection, resource management, and latency reduction. Many current studies have applied DL and ML models to diagnose/classify a patient's health status at local edge nodes that are close to sensors or devices that are generating data. This helped reduce data transfer time and resource consumption, and increased real-time execution capability.

7. Conclusion

The current state of COVID-19 has drastically changed the global landscape of the SHM Framework and the need for such systems in this difficult time. Recently, several smart healthcare architecture has been proposed for accurate screening, fever, cough and diagnosis of symptoms such as body aches and maintaining social distance. Applications based on ML, DL and big data analytics in the healthcare framework have modernized statistical analysis, live tracking of patient health status, and efficient diagnosis and treatment. This paper presented a comprehensive review of real-time SHM frameworks that are powered by cognitive computing, ML, cloud, and analytics. This study has also analyzed the AI and ubiquitous computing advances in SHM frameworks for RPM.

AI systems can be implemented at the edge using newer platforms such as Healthcare 2.0 and Industry 4.0 and integrated into SHM platforms to provide disease detection and prevention, treatment and real-time diagnostic support to patients. These architectures may also need the collaboration of cloud and fog layer. Intelligent edge nodes can be deployed in homes as well as in smart hospitals to facilitate remote interaction. Healthcare 4.0 uses CC, FC, IoT and tele-healthcare technologies [27]. Blockchain technology can be implemented in the framework to maintain information confidentiality and protect patient interests. However, the benefits of blockchain for completing the IoT-health system have not been realized [121]. All technologies are now elements of the well-known ubiquitous and smart healthcare architecture, which aims to operate with greater intelligence, reliability, privacy and efficiency. As a result, all these technologies can aid in the accelerated progress of the smart healthcare industry.

According to forecasts, the existing hospital-centric health system will shift to a 'hospital-home-balanced' model in 2021, then to a 'home-centric' model in 2030. The article [122] explained the "hospital of the

Table 4
Comparison of current state-of-art of ubiquitous and SHM frameworks.

Authors/reference	Architecture	Methods/algorithm employed	Dataset/sensors	Data features	Applicability domain	Outcomes (Metrics and Results)
[44]	3 – tier	ML classifiers, Sampling techniques	Chronic BP data with vital signs, symptoms, context and AAL data	Context aware, Multi-class and imbalanced data	Elderly and emergency healthcare	Accuracy = 76–99 % F-score = 0.26–0.99
[52]	4 – tier	NB and Whale Optimization	Chronic BP data with vital signs and symptoms.	Multi-class and imbalanced data	Elderly and emergency healthcare	Accuracy = 91.1–96.8 % Minimum features selected = 5 Accuracy = 97.1 %
[45]	3 – tier	Multinomial NB and Map-Reduce	UCI-M-HEALTH Wearable sensor data	Multi-class data	Physical activity monitoring, Elderly care delivery.	Monitoring and Alerting
[66]	4 – tier	Rule based classifier	Cardiac disorder	Context aware sensor data Binary (two-label) data	Personal health monitoring	Monitoring and Alerting
[47]	2 – tier	OCSVM	ECG data	Binary data	Health data classification	Accuracy = 92.5 %
[54]	3 – tier	k-NN	UCI dataset of Electrocardiogram (ECG) data	Small, Multi-class	Disease data classification	
[67]	3 – tier	ML algorithms: SVM, k-NN, DT, LR, DA	Pima Indians Diabetes Database.	Multivariate, Time series.	Health monitoring in smart home perspective.	SVM model Accuracy = 75 % AUC = 0.7 (approx.) MSE = 0.26, MAE = 0.29, Correlation = 0.87.
[46]	4 – tier	ANN model, Probabilistic state of vulnerability (PSoV)	Smart sensor data collected for 5 subjects.	Multi-class data	Wellness based Healthcare	Maximum F-score(%) = 79 % for Diabetes Maximum F-score(%) = 75.4 % for Mental health
[53]	3 – tier	LSTM (Deep Neural Network)	Mental health and Diabetes data of patients from Australian Hospital.	Real EHR and current data of patient.	Healthcare and monitoring	Accuracy = 89 %–95.9 %, Recall = 81.7–94.5, Precision = 89.2–92.4, F-measure = 85.1–93.4
[55]	3 – tier	Similarity coefficient, Fuzzy k-NN, J48, Random decision tree, Naïve Bayes	Adult Dataset https://archive.ics.uci.edu/ml/datasets/Adult	Multivariate data	Disease data classification	Results for Heart disease dataset using k-NN: Accuracy = 94.3, Sensitivity = 96.2, Specificity = 94.2, & F-measure = 96.7.
[56]	3 – tier	DT, SVM, NB and k-NN	Health datasets from UCI: Infectious disease and Heart disease.	Multivariate data	Smart student Healthcare monitoring, Multiple Disease data classification	Focused on Network QoS
[57]	3 – tier	Data analysis	Medical (ECG, Vital signs), Environmental and Context data	Binary	Emergency and Elderly healthcare.	
[58]	4 - Tier	Deep Learning, Cloud Analytics, Novel Loss function.	Vital signs, Symptoms and AAL data.	Imbalanced, Context aware, Multi-class Big data	Elderly and emergency healthcare, Chronic illness, RPM and recommendation	Accuracy = 84–99 % F-Score = 0.84–0.99
[59]	3 - Tier	Deep Learning	Vital signs, Symptoms and AAL data.	Imbalanced, Context aware, Multi-class Big data	Patient monitoring, Elderly and emergency healthcare, Chronic illness	Accuracy = 99.97 % F-Score = 0.91–0.99 Precision = 0.84–1 Recall = 0.79–0.89
[60]	4 – tier	NB and Firefly algorithm	Vital signs, Symptoms	Context aware AAL data, Multi-class data	Elderly and emergency healthcare	Accuracy = 90.6–99 % F-score = 0.27–0.98 %
[62]	3 – tier	SVM, Data Novelty Analysis, Bayesian Belief Network	Environmental and health dataset.	Heterogeneous data	Healthcare in Smart cities	Accuracy = 99.8 % F-measure = 0.998 Specificity = 0.99
[51]	3 – tier	SVM, NB, k-NN and DT. K-fold cross validation.	Waterborne disease related dataset of 182 students including EHR, sensor, and environment and Context data.	Multivariate data	Smart student healthcare system	DT Accuracy = 91.66 % Sensitivity = 0.9512
[61]	4 – tier	Severity Index, Bayesian classifier, k-NN, ANN and SVM	Health, Environmental and AAL data.	Heterogeneous data	Healthcare in smart office environment.	(Bayesian classifier) Accuracy = 96.5 % Sensitivity = 93.6 % F-measure = 94.3 %
[64]	3 – tier	Bayesian Belief Network (BBN) and Temporal Health Index (THI),	Health data and Environmental data from UCI repository	Temporal data of 67 patients for 30 days.	Patient monitoring, Elderly and emergency healthcare, Chronic illness.	ROC = 0.948–0.984, F-Measure = 0.848–0.911, Precision = 0.857–0.928, Recall = 0.84–0.896
[49]	3 – tier	DT, ANN, SVM and Ensemble.	Physiological, food consumption, and exercise data.	Data of 12,366 people with 757,732 dataItems. Two-class (Binary) data.	Chronic disease monitoring, diagnosis and management	Accuracy = 90 % approx.
[50]	3 – tier	Consensus clustering, “Sequential Minimal Optimization” (SMO), Bayes Net, NB Rank correlation coefficient.	ECG data of 15 subjects.	Binary, High dimensional.	Real time monitoring of cardiac health	Accuracy = 89.7 %–98.9 %; Other QoS and Energy based metrics

(continued on next page)

Table 4 (continued)

Authors/reference	Architecture	Methods/algorithm employed	Dataset/sensors	Data features	Applicability domain	Outcomes (Metrics and Results)
[65]	3 – tier	Closed loop management. k-NN	ECG – data	Temporal data	Patient monitoring, Elderly and emergency healthcare, Chronic illness.	Accuracy = 93.6 %
[63]	3 – tier	RK-PCA, FaMOORA, 2 L-2HMM, SpikQ-Net and MoSHO	Biomedical, environment and behavioral (context) data.	Heterogeneous sensor data of 50 users. Binary	Health monitoring	Detection accuracy improvement = 97 % Latency reduction = 3 ms. Execution time reduction = 1.7 ms.
[68]	2 – tier	Ensemble, LR, DT, Random Forest and XGBoost	Vital signs and motion data	Signal sensor data from RFID readers.	Mental health (suicidal behaviour)	Decision Tree: MAE = 0.01, MSE = 0.003.
[48]	2 – tier	SVM, Bayesian classification, Neural network.	Biomedical data with WBAN, Environmental data, Location and Context data with Motion sensors	Heterogeneous data, two-class data.	Elderly care in Smart Home	Helps as CDSS (Clinical Decision Support System).

future” (HoF) and considers the wireless and mobile communications as a key requirement of the HoF. New technologies, system designs, and computing paradigms are required to accomplish such evolution, predominantly in the smart e-health domains. The paradigm for smart ubiquitous healthcare systems is the result of new issues to meet multiple system needs such as dependency, low latency, mobility, energy efficiency, responsiveness, security, and more.

We believe that prospective RPM and medical care will build upon effective and reasonable implementation of ML in SHM. Application of complex algorithms for data analysis in SHM is possible, thus improving recommendations that prevent or reduce the likelihood of developing complications and enable early diagnosis of acute complications of chronic and other diseases. The vision of this research is to plan and develop ML and DL based tools for healthcare that use analytics, knowledge-driven learning, and logic-based examination to address data-to-knowledge gaps. IoT-driven tracking of everyday activities can also help healthy and active people for their well-being. In addition, the use of a cloud-based ML platform definitely improves the ability to handle Big Data. The authors [58,123] used a cloud-based ML platform (Azure) for disease classification.

This work is a part of the revolution that provides endways processing and intelligence for IoT-driven health care inventions for the prevention of CDs worldwide. The vision is to develop an understanding of “Knowledge Systems for Healthcare Applications” based on cognitive science. This comprehensive review is working to set the standard for healthcare IoT and accelerate innovation for physicians, patients, and hospitals willing to realize the feature of Analytics in SHM frameworks.

CRedit authorship contribution statement

Anand Motwani: Conceptualization, Data curation, Review Methodology, Formal analysis, Writing – original and final draft, editing, review, and Correspondence. **Piyush Kumar Shukla:** Investigation, Supervision, Editing, Visualization. **Mahesh Pawar:** Supervision, Validation, Editing.

Declaration of competing interest

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References

- [1] Zahid A, Poulsen K, Sharma R, Wingreen SC. A systematic review of emerging information technologies for sustainable data-centric health-care. *Int J Med Inform* 2021;104420.
- [2] Charulatha AR, Sujatha R. Smart healthcare use cases and applications. In: Raj P, Chatterjee JM, Kumar A, Balamurugan B, editors. *Internet of things use cases for the healthcare industry*. Cham: Springer International Publishing; 2020. p. 185–203.
- [3] Ullah H, Nair NG, Moore A, Nugent C, Muschamp P, Cuevas M. 5G communication: an overview of vehicle-to-everything, drones, and healthcare use-cases. *IEEE Access*. 2019;7:37251–68.
- [4] Din IU, Almogren A, Guizani M, Zuair M. A decade of internet of things: analysis in the light of healthcare applications. *IEEE Access* 2019;7:89967–79.
- [5] Bhatia M, Kaur S, Sood SK, Behal V. Internet of things-inspired healthcare system for urine-based diabetes prediction. *Artif Intell Med* 2020;107:101913.
- [6] Da Costa CA, Pasluosta CF, Eskofier B, Da Silva DB, da Rosa Righi R. Internet of health things: toward intelligent vital signs monitoring in hospital wards. *Artif Intell Med* 2018;89:61–9.
- [7] Lont M, Milosevic D, van Roermund A. Wireless body area networks. In: *Wake-up receiver based ultra-low-power WBAN*. Springer; 2014. p. 7–28.
- [8] Maheswar R, Kanagachidambaresan G, Jayaparvathy R, Thampi SM. Body area network challenges and solutions. *Springer*; 2019.
- [9] Shi W, Cao J, Zhang Q, Li Y, Xu L. Edge computing: vision and challenges. *IEEE Internet Things J* 2016;3:637–46.
- [10] Chen ML, Hao Wei, Qian Yixue, Humar Yongfeng, Iztok. Edge cognitive computing based smart healthcare system. *Futur Gener Comput Syst* 2018;86: 403–11.
- [11] Bajaj G, Motwani A. Improving reliability of mobile social cloud computing using machine learning in content addressable network. In: *Social networking and computational intelligence lecture notes in networks and systems*. Singapore: Springer; 2020. p. 85–103.
- [12] Li R, Wang X, Lawler K, Garg S, Bai Q, Alty J. Applications of artificial intelligence to aid detection of dementia: a scoping review on current capabilities and future directions. *J Biomed Inform* 2022;104030.
- [13] Mahdavejad MS, Rezvan M, Berekatani M, Adibi P, Barnaghi P, Sheth AP. Machine learning for internet of things data analysis: a survey. *Digit Commun Netw* 2018;4:161–75.
- [14] Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. *Future Healthc J* 2019;6:94.
- [15] Latif S, Qadir J, Farooq S, Imran MA. How 5g wireless (and concomitant technologies) will revolutionize healthcare? *Future Internet* 2017;9:93.
- [16] Amin SU, Hossain MS. Edge intelligence and internet of things in healthcare: a survey. *IEEEAccess* 2020;9:45–59.
- [17] Yuehong Y, Zeng Y, Chen X, Fan Y. The internet of things in healthcare: an overview. *J Ind Inf Integr* 2016;1:3–13.
- [18] Aghdam ZN, Rahmani AM, Hosseinzadeh M. The role of the internet of things in healthcare: future trends and challenges. *Computer methods and programs in biomedicine* 2020;199:105903.
- [20] Albahri A, Alwan JK, Taha ZK, Ismail SF, Hamid RA, Zaidan A, et al. IoT-based telemedicine for disease prevention and health promotion: state-of-the-art. *J Netw Comput Appl* 2021;173:102873.
- [21] Sadoughi F, Behmanesh A, Sayfour N. Internet of things in medicine: a systematic mapping study. *J Biomed Inform* 2020;103:103383.
- [22] Faust O, Hagiwara Y, Hong TJ, Lih OS, Acharya UR. Deep learning for healthcare applications based on physiological signals: a review. *Comput Methods Programs Biomed* 2018;161:1–13.
- [23] Purushotham S, Meng C, Che Z, Liu Y. Benchmarking deep learning models on large healthcare datasets. *J Biomed Inform* 2018;83:112–34.
- [24] Ahmadi H, Arji G, Shahmoradi L, Safdari R, Nilashi M, Alizadeh M. The application of internet of things in healthcare: a systematic literature review and classification. *Univ Access Inf Soc* 2019;18:837–69.
- [25] Pandey SK, Janghel RR. Recent deep learning techniques, challenges and its applications for medical healthcare system: a review. *Neural Process Lett* 2019; 50:1907–35.

- [26] Ray PP, Dash D, Kumar N. Sensors for internet of medical things: state-of-the-art, security and privacy issues, challenges and future directions. *Comput Commun* 2020;160:111–31.
- [27] Hathaliya JJ, Tanwar S. An exhaustive survey on security and privacy issues in healthcare 4.0. *Comput Commun* 2020;153:311–35.
- [28] Habibzadeh H, Soyata T. Toward uniform smart healthcare ecosystems: a survey on prospects, security, and privacy considerations. In: *Connected health in smart cities*. Springer; 2020. p. 75–112.
- [29] Talal M, Zaidan A, Zaidan B, Albahri A, Alamoodi A, Albahri O, et al. Smart home-based IoT for real-time and secure remote health monitoring of triage and priority system using body sensors: multi-driven systematic review. *J Med Syst* 2019;43:42.
- [30] Darwish A, Hassanien AE, Elhoseny M, Sangaiah AK, Muhammad K. The impact of the hybrid platform of internet of things and cloud computing on healthcare systems: opportunities, challenges, and open problems. *J Ambient Intell Humaniz Comput* 2019;10:4151–66.
- [31] Moher D, Liberati A, Tetzlaff J, Altman DG, Group P. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS medicine* 2009;6:e1000097.
- [32] Mistry I, Tanwar S, Tyagi S, Kumar N. Blockchain for 5G-enabled IoT for industrial automation: a systematic review, solutions, and challenges. *Mech Syst Signal Process* 2020;135:106382.
- [33] Brock DL. The electronic product code (epc). In: *Auto-ID center white paper MIT-AUTOID-WH-002*; 2001. p. 1–21.
- [34] Ashton K. That 'internet of things' thing. *RFID J* 2009;22:97–114.
- [35] Roco MC, Bainbridge WS. *Converging technologies for improving human performance: nanotechnology, biotechnology, information technology and cognitive science*. Springer Science & Business Media; 2013.
- [36] Strategy I, Unit P. In: *ITU internet reports 2005: the internet of things*. 1. Geneva: International Telecommunication Union; 2005. p. 62.
- [37] Malasinghe LP, Ramzan N, Dahal K. Remote patient monitoring: a comprehensive study. *J Ambient Intell Humaniz Comput* 2019;10:57–76.
- [38] Al Hemaury M, Serhani M, Amin S, Alahmad M. A comprehensive framework for elderly healthcare monitoring in smart environment. In: *Technology for smartFutures*; 2018. p. 113–40.
- [39] Mohammed K, Zaidan A, Zaidan B, Albahri O, Alsalem M, Albahri A, et al. Real-time remote-health monitoring systems: a review on patients prioritisation for multiple-chronic diseases, taxonomy analysis, concerns and solution procedure. *J Med Syst* 2019;43:1–21.
- [40] Dang LM, Piran M, Han D, Min K, Moon H. A survey on internet of things and cloud computing for healthcare. *Electronics* 2019;8:768.
- [41] Gardašević G, Katzis K, Bajić D, Berbakov L. Emerging wireless sensor networks and internet of things technologies—foundations of smart healthcare. *Sensors* 2020;20:3619.
- [42] Adibi S. A mobile health network disaster management system. In: *2015 seventh international conference on ubiquitous and future networks*. IEEE; 2015. p. 424–8.
- [43] Hernandez N, Castro L, Medina-Quero J, Favela J, Michan L, Mortenson WB. Scoping review of healthcare literature on mobile, wearable, and textile sensing technology for continuous monitoring. *Journal of healthcare informaticsResearch* 2021;1–30.
- [44] Hassan MK, El Desouky AI, Elghamrawy SM, Sarhan AM. Intelligent hybrid remote patient-monitoring model with cloud-based framework for knowledge discovery. *Comput Electr Eng* 2018;70:1034–48.
- [45] Syed L, Jabeen S, Manimala S, Alsaeedi A. Smart healthcare framework for ambient assisted living using IoT and big data analytics techniques. *Future Gener Comput Syst* 2019;101:136–51.
- [46] Bhatia M, Sood SK. A comprehensive health assessment framework to facilitate IoT-assisted smart workouts: a predictive healthcare perspective. *Comput Ind* 2017;92:50–66.
- [47] Krishnan S, Lokesh S, Devi MR. An efficient Elman neural network classifier with cloud supported internet of things structure for health monitoring system. *Comput Netw* 2019;151:201–10.
- [48] Jung Y. Hybrid-aware model for senior wellness service in smart home. *Sensors* 2017;17:1182.
- [49] Chen M, Yang J, Zhou J, Hao Y, Zhang J, Youn C-H. 5G-smart diabetes: toward personalized diabetes diagnosis with healthcare big data clouds. *IEEE Commun Mag* 2018;56:16–23.
- [50] Abawajy JH, Hassan MM. Federated internet of things and cloud computing pervasive patient health monitoring system. *IEEE CommunMag* 2017;55:48–53.
- [51] Verma P, Sood SK, Kalra S. Cloud-centric IoT based student healthcare monitoring framework. *J Ambient Intell Humaniz Comput* 2018;9:1293–309.
- [52] Hassan MK, El Desouky AI, Elghamrawy SM, Sarhan AM. A hybrid real-time remote monitoring framework with NB-WOA algorithm for patients with chronic diseases. *Futur Gener Comput Syst* 2019;93:77–95.
- [53] Pham T, Tran T, Phung D, Venkatesh S. Predicting healthcare trajectories from medical records: a deep learning approach. *J Biomed Inform* 2017;69:218–29.
- [54] Moghadas E, Rezaeizadeh J, Farahbakhsh R. An IoT patient monitoring based on fog computing and data mining: cardiac arrhythmia usecase. *Internet Things* 2020;11:100251.
- [55] Vijayakumar V, Malathi D, Subramaniaswamy V, Saravanan P, Logesh R. Fog computing-based intelligent healthcare system for the detection and prevention of mosquito-borne diseases. *Comput Hum Behav* 2019;100:275–85.
- [56] Verma P, Sood SK. Cloud-centric IoT based disease diagnosis healthcare framework. *J Parallel Distrib Comput* 2018;116:27–38.
- [57] Rahmani AM, Gia TN, Negash B, Anzanpour A, Azimi I, Jiang M, et al. Exploiting smart e-health gateways at the edge of healthcare internet-of-things: a fog computing approach. *Futur Gener Comput Syst* 2018;78:641–58.
- [58] Motwani A, Shukla PK, Pawar M. Novel framework based on deep learning and cloud analytics for smart patient monitoring and recommendation (SPMR). *Journal of Ambient Intelligence and Humanized Computing* 2021:1–16.
- [59] Motwani A, Shukla PK, Pawar M. Smart predictive healthcare framework for remote patient monitoring and recommendation using deep learning with novel cost optimization. In: *International conference on information and communication technology for intelligent systems*. Springer; 2020. p. 671–82.
- [60] Hassan MK, El Desouky AI, Badawy MM, Sarhan AM, Elhoseny M, Gunasekaran M. EoT-driven hybrid ambient assisted living framework with naive Bayes–firefly algorithm. *Neural Comput Applic* 2019;31:1275–300.
- [61] Bhatia M, Sood SK. Exploring temporal analytics in fog-cloud architecture for smart office healthcare. *Mob Netw Appl* 2019;24:1392–410.
- [62] Sood SK. Fog-cloud centric IoT-based cyber physical framework for panic oriented disaster evacuation in smart cities. *Earth Sci Inf* 2020;1–22.
- [63] Ijaz M, Li G, Wang H, El-Sherbeeney AM, Moro Awelishah Y, Lin L, et al. Intelligent fog-enabled smart healthcare system for wearable physiological parameter detection. *Electronics* 2020;9:2015.
- [64] Verma P, Sood SK. Fog assisted-IoT enabled patient health monitoring in smart homes. *IEEE Internet Things J* 2018;5:1789–96.
- [65] Azimi I, Anzanpour A, Rahmani AM, Pahikkala T, Levorato M, Liljeberg P, et al. HiCH: hierarchical fog-assisted computing architecture for healthcare IoT. *ACM Trans Embedd Comput Syst* 2017;16:1–20.
- [66] Esposito M, Minutolo A, Megna R, Forastiere M, Magliulo M, De Pietro G. A smart mobile, self-configuring, context-aware architecture for personal health monitoring. *Eng Appl Artif Intel* 2018;67:136–56.
- [67] Chatrati SP, Hossain G, Goyal A, Bhan A, Bhattacharya S, Gaurav D, et al. Smart home health monitoring system for predicting type 2 diabetes and hypertension. *J King Saud Univ - Comput Inf Sci* 2022;34:862–70.
- [68] Tao X, Shaik TB, Higgins N, Gururajan R, Zhou X. Remote patient monitoring using radio frequency identification (RFID) technology and machine learning for early detection of suicidal behaviour in mental health facilities. *Sensors* 2021;21:776.
- [69] Mardini MT, Iraqi Y, Agoulmine N. A survey of healthcare monitoring systems for chronically ill patients and elderly. *J Med Syst* 2019;43:50.
- [70] Albahri O, Albahri A, Mohammed K, Zaidan A, Zaidan B, Hashim M, et al. Systematic review of real-time remote health monitoring system in triage and priority-based sensor technology: taxonomy, open challenges, motivation and recommendations. *J Med Syst* 2018;42:1–27.
- [71] Baig MM, GholamHosseini H, Moqem AA, Mirza F, Lindén M. A systematic review of wearable patient monitoring systems—current challenges and opportunities for clinical adoption. *J Med Syst* 2017;41:1–9.
- [72] Kashani MH, Madanipour M, Nikravan M, Asghari P, Mahdipour E. A systematic review of IoT in healthcare: applications, techniques, and trends. *J Netw Comput Appl* 2021;192:103164.
- [73] Michalakakis K, Caridakis G. IoT contextual factors on healthcare. In: *GeNeDis 2016*. Springer; 2017. p. 189–200.
- [74] Liu L, Shah SA, Zhao G, Yang X. Respiration symptoms monitoring in body area networks. *Appl Sci* 2018;8:568.
- [75] Safaei M, Asadi S, Driss M, Boulila W, Alsaeedi A, Chizari H, et al. A systematic literature review on outlier detection in wireless sensor networks. *Symmetry* 2020;12:328.
- [76] Safaei M, Ismail AS, Chizari H, Driss M, Boulila W, Asadi S, et al. Standalone noise and anomaly detection in wireless sensor networks: a novel time-series and adaptive bayesian-network-based approach. *Softw Pract Exp* 2020;50:428–46.
- [77] Shadroo S, Rahmani AM. Systematic survey of big data and data mining in internet of things. *Comput Netw* 2018;139:19–47.
- [78] Tripathi G, Abdul Ahad M, Paiva S. Sms: a secure healthcare model for smart cities. *Electronics* 2020;9:1135.
- [79] Oueida S, Kotb Y, Aloqaily M, Jararweh Y, Baker T. An edge computing based smart healthcare framework for resource management. *Sensors* 2018;18:4307.
- [80] Bonomi F, Milito R, Zhu J, Addepalli S. Fog computing and its role in the internet of things. In: *Proceedings of the first edition of the MCC workshop on mobile cloud computing*; 2012. p. 13–6.
- [81] Hassan MK, El Desouky AI, Elghamrawy SM, Sarhan AM. Big data challenges and opportunities in healthcare informatics and smart hospitals. In: *Security in smart cities: models, applications, and challenges*. Springer; 2019. p. 3–26.
- [82] Sakr S, Elgammal A. Towards a comprehensive data analytics framework for smart healthcare services. *Big Data Res* 2016;4:44–58.
- [83] Kumari P, Mathew L, Syal P. Increasing trend of wearables and multimodal interface for human activity monitoring: a review. *Biosens Bioelectron* 2017;90:298–307.
- [84] Raja K, Saravanan S, Anitha R, Priya SS, Subhashini R. Design of a low power ECG signal processor for wearable health system—review and implementation issues. In: *2017 11th international conference on intelligent systems and control (ISCO)*. IEEE; 2017. p. 383–7.
- [85] Kaappa ES, Joutsen A, Cömert A, Vanhala J. The electrical impedance measurements of dry electrode materials for the ECG measuring after repeated washing. *Research Journal of Textile and Apparel* 2017;21(1):59–71.
- [86] Shah SA, Fioranelli F. RF sensing technologies for assisted daily living in healthcare: a comprehensive review. *IEEE Aerosp Electron Syst Mag*. 2019;34:26–44.
- [87] Thomas SS, Nathan V, Zong C, Soundarapandian K, Shi X, Jafari R. BioWatch: a noninvasive wrist-based blood pressure monitor that incorporates training

- techniques for posture and subject variability. *IEEE J Biomed Health Inform* 2015;20:1291–300.
- [88] Rault T, Bouabdallah A, Challal Y, Marin F. A survey of energy-efficient context recognition systems using wearable sensors for healthcare applications. *Pervasive Mob Comput* 2017;37:23–44.
- [89] Chung K, Park RC. Cloud based u-healthcare network with QoS guarantee for mobile health service. *Clust Comput* 2019;22:2001–15.
- [90] Mutlag AA, Abd Ghani MK, Na Arunkumar, Mohammed MA, Mohd O. Enabling technologies for fog computing in healthcare IoT systems. *Futur Gener Comput Syst* 2019;90:62–78.
- [91] Coronato A, Naeem M, De Pietro G, Paragliola G. Reinforcement learning for intelligent healthcare applications: a survey. *Artif Intell Med* 2020;109:101964.
- [92] Suryani V. A survey on trust in Internet of Things. In: 2016 8th international conference on information technology and electrical engineering (ICITEE). IEEE; 2016. p. 1–6.
- [93] Matharu GS, Upadhyay P, Chaudhary L. The internet of things: challenges & security issues. In: 2014 international conference on emerging technologies (ICET). IEEE; 2014. p. 54–9.
- [94] Hatzivasilis G, Soultatos O, Ioannidis S, Verikoukis C, Demetriou G, Tsatsoulis C. Review of security and privacy for the internet of medical things (IoMT). In: 2019 15th international conference on distributed computing in sensor systems (DCOSS). IEEE; 2019. p. 457–64.
- [95] Alabdulatif A, Khalil I, Yi X, Guizani M. Secure edge of things for smart healthcare surveillance framework. *IEEE Access* 2019;7:31010–21.
- [96] El-Sappagh S, Ali F, El-Masri S, Kim K, Ali A, Kwak K-S. Mobile health technologies for diabetes mellitus: current state and future challenges. *IEEE Access* 2018;7:21917–47.
- [97] Hu Y-H, Lin W-C, Tsai C-F, Ke S-W, Chen C-W. An efficient data preprocessing approach for large scale medical data mining. *Technol Health Care* 2015;23:153–60.
- [98] Zhang B, Cao P. Classification of high dimensional biomedical data based on feature selection using redundant removal. *PloS one* 2019;14:e0214406.
- [99] Aziz R, Verma C, Srivastava N. A fuzzy based feature selection from independent component subspace for machine learning classification of microarray data. In: *Genomics Data*. 8; 2016. p. 4–15.
- [100] Motwani A, Shukla PK, Pawar M. Novel machine learning model with wrapper-based dimensionality reduction for predicting chronic kidney disease risk. In: *Soft computing and signal processing*. Springer; 2021. p. 29–37.
- [101] Chen P-HC, Liu Y, Peng L. How to develop machine learning models for healthcare. *Nat Mater* 2019;18:410–4.
- [102] Desai SB, Pareek A, Lungren MP. Deep learning and its role in COVID-19 medical imaging. *IntellBased Med* 2020;3:100013.
- [103] Lee CS, Lee AY. Clinical applications of continual learning machine learning. *Lancet Digit Health* 2020;2:e279–81.
- [104] Vokinger KN, Feuerriegel S, Kesselheim AS. Continual learning in medical devices: FDA's action plan and beyond. *Lancet Digit. Health* 2021;3:e337–8.
- [105] Pianykh OS, Langs G, Dewey M, Enzmann DR, Herold CJ, Schoenberg SO, et al. Continuous learning AI in radiology: implementation principles and early applications. *Radiology* 2020;297:6–14.
- [106] Hassabis D, Kumaran D, Summerfield C, Botvinick M. Neuroscience-inspired artificial intelligence. *Neuron* 2017;95:245–58.
- [107] Hassler AP, Menasalvas E, García-García FJ, Rodríguez-Mañas L, Holzinger A. Importance of medical data preprocessing in predictive modeling and risk factor discovery for the frailty syndrome. *BMC Med Inform Decis Mak* 2019;19:1–17.
- [108] Aldahiri A, Alrashed B, Hussain W. Trends in using IoT with machine learning in health prediction system. *Forecasting* 2021;3:181–206.
- [109] Amador T, Saturnino S, Veloso A, Ziviani N. Early identification of ICU patients at risk of complications: regularization based on robustness and stability of explanations. *Artif Intell Med* 2022;128:102283.
- [110] Mohammad MN, Shima T, Elaheh H. Adaptive and personalized user behavior modeling in complex event processing platforms for remote health monitoring systems. *Artif Intell Med* 2022;102421.
- [111] Rasheed K, Qayyum A, Ghaly M, Al-Fuqaha A, Razi A, Qadir J. Explainable, trustworthy, and ethical machine learning for healthcare: a survey. *Comput Biol Med* 2022;149:1–23.
- [112] Kim M, Yun J, Cho Y, Shin K, Jang R, Bae H-J. Deep learning in medical imaging. *Neurospine* 2019;16:657.
- [113] Shah P, Kendall F, Khozin S, Goosen R, Hu J, Laramie J, et al. Artificial intelligence and machine learning in clinical development: a translational perspective. *npj Digit Med* 2019;2:1–5.
- [114] Amann J, Blasimme A, Vayena E, Frey D, Madai VI. Explainability for artificial intelligence in healthcare: a multidisciplinary perspective. *BMC Med Inform Decis Mak* 2020;20:1–9.
- [115] Vellido A. The importance of interpretability and visualization in machine learning for applications in medicine and health care. *Neural Comput Appl* 2020;32:18069–83.
- [116] Serhani MA, Ismail H, Nujum Navaz A, T El Kassabi H. ECG monitoring systems: review, architecture, processes, and key challenges. *Sensors* 2020;20:1796.
- [117] Hegde C, Jiang Z, Suresha PB, Zello J, Seyedi S, Smith MA, et al. Autotriage-an open source edge computing raspberry pi-based clinical screening system. *medRxiv* 2020:1–13. <https://doi.org/10.1101/2020.04.09.20059840>. In preparation.
- [118] Maghded HS, Ghafoor KZ, Sadiq AS, Curran K, Rawat DB, Rabie K. A novel AI-enabled framework to diagnose coronavirus COVID-19 using smartphone embedded sensors: design study. In: 2020 IEEE 21st international conference on information reuse and integration for data science (IRI). IEEE; 2020. p. 180–7.
- [119] Hossain MS, Muhammad G, Guizani N. Explainable AI and mass surveillance system-based healthcare framework to combat COVID-19 like pandemics. *IEEE Netw* 2020;34:126–32.
- [120] Ahmed E, Yaqoob I, Hashem IAT, Khan I, Ahmed AIA, Imran M, et al. The role of big data analytics in internet of things. *Comput Netw* 2017;129:459–71.
- [121] Hu L, Qiu M, Song J, Hossain MS, Ghoneim A. Software defined healthcare networks. *IEEE Wirel Commun* 2015;22:67–75.
- [122] Ahmed I, Karvonen H, Kumpuniemi T, Katz M. Wireless communications for the hospital of the future: requirements, challenges and solutions. *Int J Wireless Inf Networks* 2020;27:4–17.
- [123] Nathaniel S, Motwani A, Saxena A. Cloud based predictive model for detection of 'chronic kidney disease' risk. *Int J Comput Sci Eng* 2018;6:185–8.