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Review

Artificial Intelligence, Sensors and Vital Health Signs: A Review

Sahalu Balarabe Junaid [1], Abdullahi Abubakar Imam [2,*], Aliyu Nuhu Shuaibu [3,4,*], Shuib Basri [5], Ganesh Kumar [5], Yusuf Alhaji Surakat [6], Abdullateef Oluwagbemiga Balogun [5,7], Muhammad Abdulkarim [1], Aliyu Garba [1], Yusra Sahalu [8], Abdullahi Mohammed [1], Yahaya Tanko Mohammed [1], Bashir Abubakar Abdulkadir [9], Abdullah Alkali Abba [10], Nana Aliyu Iliyasu Kakumi [11] and Ammar Kareem Alazzawi [12]

1 Department of Computer Science, Ahmadu Bello University, Zaria 810107, Nigeria
2 School of Digital Science, Universiti Brunei Darussalam, Brunei Darussalam, Jalan Tungku Link, Gadong BE1410, Brunei
3 Department of Electrical Engineering, University of Jos, Bauchi Road, Jos 930105, Nigeria
4 Department of Electrical, Telecommunications and Computer Engineering, Kampala International University, Kampala 759125, Uganda
5 Computer and Information Science Department, Universiti Teknologi PETRONAS, Sri Iskandar 32610, Malaysia
6 Department of Family Medicine, University Medical Centre, Ahmadu Bello University, Zaria 810107, Nigeria
7 Department of Computer Science, University of Ilorin, Ilorin 240003, Nigeria
8 SEHA Abu Dhabi Health Services Co., Abu Dhabi 109090, United Arab Emirates
9 Department of Chemistry, Gombe State University, Gombe 760253, Nigeria
10 Institute of Health Science, Kaduna State University, Kaduna 800212, Nigeria
11 Patient Care Department, General Ward, Saudi German Hospital Cairo, Taha Hussein Rd, Huckstep, El Nozha, Cairo 4473303, Egypt
12 Computer Techniques Engineering Department, Al-Mustaqbal University College, Babylon 51001, Iraq
* Correspondence: abdullahi.imam@ubd.edu.bn (A.A.I.); nuhua@unijos.edu.ng (A.N.S.)

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Abstract: Large amounts of patient vital/physiological signs data are usually acquired in hospitals manually via centralized smart devices. The vital signs data are occasionally stored in spreadsheets and may not be part of the clinical cloud record; thus, it is very challenging for doctors to integrate and analyze the data. One possible remedy to overcome these limitations is the interconnection of medical devices through the internet using an intelligent and distributed platform such as the Internet of Things (IoT) or the Internet of Health Things (IoHT) and Artificial Intelligence/Machine Learning (AI/ML). These concepts permit the integration of data from different sources to enhance the diagnosis/prognosis of the patient's health state. Over the last several decades, the growth of information technology (IT), such as the IoT/IoHT and AI, has grown quickly as a new study topic in many academic and business disciplines, notably in healthcare. Recent advancements in healthcare delivery have allowed more people to have access to high-quality care and improve their overall health. This research reports recent advances in AI and IoT in monitoring vital health signs. It investigates current research on AI and the IoT, as well as key enabling technologies, notably AI and sensors-enabled applications and successful deployments. This study also examines the essential issues that are frequently faced in AI and IoT-assisted vital health signs monitoring, as well as the special concerns that must be addressed to enhance these systems in healthcare, and it proposes potential future research directions.

Keywords: vital signs; healthcare; sensors; machine learning; Internet of Things; artificial intelligence

1. Introduction

The advancement of information technology (IT) has resulted in significant improvements in healthcare services, particularly in remote health monitoring. Among the primary purposes of employing physical sensor networks is focusing on illness prevention and prompt identification of critical diseases. Today, smart technologies and sophisticated instruments (such as smart wireless and wearable sensors) have substantially risen for rapid monitoring and control of patients' situations via prompt access and continuous assessment of patients' vital health signs.

The capacity of such smart devices to store and transport data is critical in several disciplines of healthcare (for example, telemedicine). Wearable sensors are primarily applied for observing patients' symptoms and health status through telemedicine, monitoring the medical facility, surgical smart robots, and a variety of other systems. In other words, the vital health signs represent the patient's physiological status, organ activity, and illness progression. The assessment of these indicators has a significant influence on illness prevention, diagnosis, treatment, and nursing care. These signals, if assessed accurately and promptly, might provide a useful recommendation for efficient and high-quality telemedicine rehabilitation. Various smart devices and AI-based systems have been developed (for example, telemedicine) to enhance vital health signs' prompt and continuous measurement. Smart devices, specifically wearable sensors, have received a lot of attention in the last decade, mostly in the healthcare field. Such devices seek to derive therapeutically important information from physiological body signals, for instance, heart rate (HR), blood pressure (BP), body temperature (BT), respiration rate (RR), oxygen saturation (SPO2), etc. Wearable sensor networks (WSNs) are made up of a variety of biological sensors [1] that are attached to various parts of the human body. Each of these sensors has unique criteria for identifying and recording symptoms [2]. Since many illnesses and impairments need continuous monitoring in the modern day, patient monitoring continuity for prompt intervention is vital. As a result, using WSNs to monitor patients is among the most significant uses of IoT technology in the medical profession.

Furthermore, the perfect alliance of AI and healthcare has morphed into improved patient care in areas ranging from clinical productivity and patient safety to medical treatment quality [3]. AI as a tool or technology is applied in data collection, storage, processing, and patient results presentation for health information management [4]. The research works on the influence of AI on medical outcomes have been beneficial and encouraging [5]. For example, caregivers and patients are increasingly utilizing and managing medical applications and games not only to observe the patients' health status but also for patient education/medical awareness [6]. This phenomenon is observed in the increase in physicians and patients adopting such platforms for patient empowerment (patient–patient) and more equitable dialogue (doctor-patient) and, more importantly, the use of cloud computing to enhance access to clinical data and the administration and use of health resources [6,7]. In terms of information, patients' health data are required to tailor patient treatment and illness prediction and healthcare policymaking through big data analytics. The internet of things (IoT) as a tool is built on cloud computing that is being used to promote healthcare delivery, brought forth by the Fourth Industrial Revolution. The success of the IoT in various application domains serves as an indicator of its acceptance and integration with wearable sensors for healthcare monitoring and delivery. Wearable sensors are used as objects or components in the IoT and are controlled via the internet. Consequently, this study examines and evaluates the current literature on the use of smart wearable sensors and AI for vital health signs. Specifically, a comprehensive examination of the use of these disruptive technologies (sensors and AI) for analyzing vital health signs is conducted.

The remainder of this paper is structured as follows: Section 2 presents a detailed analysis of existing related studies. Section 3 presents the review method and strategy utilized in this research work. The application of IoT and AI in healthcare delivery is presented in Sections 4 and 5 respectively. Section 6 looks at future research directions while Section 7 concludes this research work.

2. Related Works

A systematic literature search and analysis of the evolving IoT cloud-based concept for IoT in healthcare was proposed in [8]. Certain challenges in managing clinical information and patient data were pointed out, including privacy and security, due to the vulnerability of IoT implementations. The difficulty of having readily established connectivity between IoT devices to obtain real-time data creation and collection, the complexities that arise in managing health devices due to the wide differences in clinical equipment, sensors, wearable devices, operating systems, and platforms, the legal and social considerations of the storage and use of data, as well as the large amount of data generated within the healthcare system will demand that attention be paid to cloud storage, data processing, and transportation. In this system, vital health signs parameters, such as temperature, respiration, and pulse, are measured using sensors. The data from these sensors are then sent to electronic health (E-health) platform that intelligently uses the obtained data to connect patients to a corresponding doctor who has access to the patients' data and can give recommendations, medications, and prescriptions. Other systems reviewed in this work include the application of the IoT in healthcare delivery, low-cost IoT-based communication technologies for monitoring the vital signs of patients in hospitals, and wirelessly sending the data to doctors in a remote location for further analysis. An IoT-based health application reminder may be used to remind patients of the appropriate medication to take and the right time to take them. Additionally, an IoT system may be designed to track the conditions of soldiers in military operations.

In a review of the IoT and its application in healthcare [9], several IoT-based techniques, such as radio frequency identification (RFID), internet protocols, Bluetooth, WSN, and Zigbee, were mentioned, and different IoT platforms implemented for healthcare applications were reviewed by the authors. One of the reviewed systems and applications includes a remote patient monitoring system that is a combination of RFID and IoT technology that constantly monitors patients using medical sensors that collect vital signs data from patients and send them to processing centers (cloud storage) through communication devices. Analytics devices are then used to process the data for further clinical actions. Another is an IoT-based health platform that uses an intelligence system that consists of three components, iMedbox, iMedPack, and Bio-Patch, which work together to facilitate medication management and monitor patients′ health symptoms. A third system is a body temperature management system that helps track and monitor human BT. In the reviewed systems and applications, the vital sign measuring devices recorded body weight, blood glucose, HR, and BP.

In a comprehensive literature review presented in [10] on the application of the IoT in vital signs monitoring, a qualitative analysis of several research articles focusing on the use of wearable body sensors/IoT for health monitoring was conducted from different perspectives, such as the publication years, sensor type, sample sizes, context, approach, and participant demographics. Some disadvantages in research analysis concerning both sample size and participant demographics that affected the outcomes were identified. In the review, seventy-three articles published between 2010 and 2019 relating to heart diseases, gait and fall, diabetes, physical activity recognition, rehabilitation, stress, and sleep were considered. Some of the shortcomings identified were that most of the reviews focused on gait and fall, and simulations included very few participants who were more likely to experience abnormal gait and sleeping disturbances. The majority of the works did not study the ideal sensor functionality, which affects the results outcomes. Among the reviewed works on cardiovascular diseases, only a few studies provided details on the patient′s gender; the notable differences between men and women make this an important factor affecting the validity of the results. Concerning the population samples in the analyzed studies, 56% conducted their studies with up to twenty samples of the data, and only 20% of the works conducted their analysis with fifty-one samples. Therefore, the less amount of data used is a shortcoming, and it was recommended that further studies should use larger data.

Similarly, in [11], the results of the performance of traditional threshold-based alarm frameworks that are used to analyze physiological parameters were studied. The study data were obtained from adult participants who were admitted to the clinical ward after elective major surgery in the Netherlands (Amsterdam University Medical Centre, Amsterdam, Netherlands) between 2018 and 2019. Data were obtained from a total of sixty participants, of which twenty-one were exempted from the analysis due to the unavailability of wireless vital signs devices. The results obtained in this study revealed that the-state-of-the-art classical threshold-based alarm system recognized anomalies in vital signs before or after treatment in the majority of the observed adverse events in ward patients and recommended the development of several methods for adaptive alarm thresholds may enhance the recognition of clinical deterioration at early stages in ward patients.

An IoT-based ambulatory vital signs data transfer system was proposed by [12], and a prototype model of the proposed system was developed using an IoT-based medical sensor board and a Linux server imitating the conventional hospital server. This proposed system was designed to transmit the vital health signs of various patients to a remote location server for possible emergency handling by physicians. The system also displays the data of multiple patients on a screen for visual observation and analysis. The recorded vital signs data of the patients are also sent to a smart IoT device, where the results are presented in a graphical form for easy analysis. For this proposed system, it was assumed that mobile connectivity would be available during any emergency, but because a disaster could be of different degrees, and cellular activity can be affected during certain disasters, this system may be ineffective.

Another interesting review [1] aimed at finding the optimum approach for implementing an IoT health monitoring platform. In their work, eighteen different articles published between 2016 and 2018 were reviewed, and it was recommended that the use of health monitoring systems that use wearable sensors and smart-watches, as studied in the papers reviewed, was a low-cost solution to health monitoring in general, and the tendency of doctors to monitor every symptom and vital signs at the hospital, most of which are not done in real-time due to a lack of capable medical personnel, can greatly affect the general outcome of the clinical processes. It was also reported that the photoplethysmogram (PPG) sensor was the best sensor; it has a low error rate, is small in size, and is widely adopted in physiological parameter measurement. In addition, the PPG sensor detects early vital signs and symptoms of health problems.

A contactless radar-based sensor for vital signs monitoring was presented in [13]. The proposed system can be deployed to monitor the vital signs (heartbeat and respiration) of multiple patients in a real-world setting. It does not need a wearable device for its operation. In addition, two algorithms were developed for target tracking and rejection of random body movements. The system can also keep track of individuals during movement. The experiments for the proposed system were carried out in two environments: a laboratory and an office area. The equipment used was a radar module, a digital signal processor/field-programmable gate array (DSP/FPGA) board, an analogue-to-digital converter (ADC), and a laptop. The system is also believed to have other potential applications, including people counting, fall detection, activity level, and human gait recognition.

Another work based on rehabilitation in telemedicine [14] presented the physiological parameters of smart wearable devices. The effects of wearable medical devices on vital sign monitoring were explored. For this research, sixty patients of young ages were chosen from the medical ward using common vital signs such as heart rate, body temperature, blood pressure, and oxygen saturation. From the analysis of the data, it was concluded that the wearable medical devices (WMDs) and the traditional devices had similar accuracy in the monitoring and measuring of vital signs, but the WMDs had better efficiency, quality, and safety and could automatically import data in a few seconds, eliminating error rate and time complexity. It was further recommended that to improve the performance of WMDs in telemedicine rehabilitation, future research should select patients from different departments, the vital signs should be divided into different levels for hierarchical analysis, and the performance of the WMDs should be evaluated using repeatable and constant measurements.

A systematic literature review (SLR) [15] reported on the application of wearable IoT sensors for monitoring the physiological parameters of patients during epidemics. The review presented AI-based wearable sensors for disease control and vital sign monitoring in epidemic outbreaks. According to this study, wearable smart technologies can monitor the physiological vital signs of patients in epidemic outbreaks. It also concluded that IoT smart sensors are suitable systems that make monitoring and detecting patients′ conditions easier for healthcare providers such as physicians, nurses, and specialists and have the greatest potential for diagnosing and monitoring the early signs of epidemic diseases. Therefore, using suitable technological IoT-based solutions could greatly enhance the control of epidemic disease as well as the application of sensors for the continuous monitoring of vital signs.

In another study, [16] presented an intelligent healthcare service for monitoring vital signs. The proposed system can be used to generate a report on the health conditions and vital signs of individuals. For evaluation, six participants from Spain and Slovenia (three from each) utilized the proposed system for about eight weeks in their homes to monitor their health. The basic metrics such as sensitivity, specificity, and total accuracy of the system achieved during this period of testing by the participants were 90%, 97%, and 96%, respectively. A light version of the proposed framework was applied through a project named SAAPHO; four sensor devices for healthcare were implemented in the framework. The devices monitored BP, blood glucose, weight, and activity and were connected to an Android device via Bluetooth, through which the sensor measurements were obtained and sent to the cloud storage. The remote data were then analyzed, and a decision was taken by doctors or clinicians, and feedback, recommendations, alarms, and reminders were then generated and provided to the user.

Recently, another IoT-based wearable device designed for the observation of quarantined remote coronavirus disease (COVID-19) patients was proposed [17]. This system is designed to measure various vital signs related to COVID-19 by monitoring the real-time geolocation positioning system (GPS) data (geographical information) of potentially infected patients. One significant aspect of this proposed system is that it provides medical authorities with useful geographical and health-care data of potentially infected people that can be stored in a database and used to predict and analyze the situation. The vital signs considered in this proposal are pulse rate, temperature, and oxygen saturation. These signs are regarded as the main symptoms of COVID-19 infection, with a temperature greater than 38 °C, heart rate measured at 100 bpm, and oxygen saturation as 92–96% indicating possible virus infection. A built-in microphone was also implemented to capture samples of cough sounds which are then processed through an AI model to aid in the monitoring of potentially infected patients. An automated health care system such as this can greatly reduce stress and provide a means of communication between doctors, medical authorities, and family respondents, and serve as a tool to collect and analyze the data needed to monitor and control the social life of patients and manage them during the pandemic era.

Additionally, [18] surveyed edge IoT in healthcare. Edge intelligence, which is a combination of AI and edge computing that targets health data classification by tracking and identifying vital signs using state-of-the-art deep learning (DL) techniques, was examined. A comprehensive analysis of the use of cutting-edge AI-based classification and prediction techniques employed for edge intelligence, as well as its many advantages, was carried out. The study also offered a brief overview of the general usage of IoT solutions in edge platforms for medical treatment and healthcare. The study considered research on physiological health data analysis, edge-based IoT systems for rehabilitation, skin disease detection, and diet monitoring, epidemic prevention systems, and research studies on diabetes treatments. Machine learning (ML), as well as big data and blockchain in IoT-based healthcare frameworks, was also studied.

In another comprehensive review, [19] introduced the concept of the Internet of Health Things (IoHT) and its application for intelligent vital health signs monitoring in hospital wards. The suggested concept focuses on surveying the different approaches that could be applied to gathering and combining vital signs data in hospitals. Some common heuristic approaches, such as weighted early warning scoring systems and the possibility of employing intelligent algorithms, were considered. Different vital signs were also discussed, including BP, BT, HR, RR, SPO2, and urine output. It was reported that the first five physiological parameters mentioned were the common parameters measured in the human body. It is believed that the development and general adoption of the IoHT concept for the analysis of physiological parameters will lead to the possibility of predicting imminent and critical problems associated with humans, making it easy for caregivers to analyze vital health signs even via remote locations.

Similarly, [7] presented a survey on the IoT and cloud computing for healthcare. The survey considered how disruptive technologies such as cloud computing, ambient assisted living, big data, and wearables are being applied to solve various issues in the healthcare industry. Various IoT, health regulations, and policies were also analyzed to determine how well they promote the sustainable development of IoT and cloud computing in the healthcare industry. Specifically, an in-depth review of IoT privacy and security issues, such as potential threats, attack types, and security setups, was carried out from a healthcare viewpoint, and an analysis of previous well-known security models was also conducted to deal with security risks and provide trends and highlight opportunities, as well as challenges for the future development of IoT-based health care [20] conducted a comprehensive review of critical healthcare and specific vital signs of patient monitoring. Several clinical issues to consider when measuring vital signs were described. They argued that medical personnel have relied on five vital signs (BT, HR, BP, RR, and SPO2) to assess the health condition of their patients. However, due to the advancement in healthcare, these vital signs may not be adequate to identify those with health issues. A conclusion was made that the interpretation of vital sign data from assessments is vital in determining the level of care a patient needs as well as providing treatment and preventing the deterioration of a patient's health from a preventable cause. It was also concluded that as patients in hospitals today are sicker than patients in the past, nurses and medical personnel can no longer rely on the traditional five vital signs to identify clinical changes in their patients. Medical personnel must know how to measure these vital signs accurately and also know how to interpret and act on them. In addition to the traditional five vital signs, they should also incorporate additional vital signs such as pain, level of consciousness, and urine output when performing assessments of their patients.

Recent developments in technology and connectivity have led to the emergence and application of IoT and AI applications in many domains. [21] presented the understanding of the role of AI in the continuous use of the Internet of Medical Things (IoMT) in healthcare. They examine the continuous intention of healthcare professionals to use the IoMT integrated with AI. [22] designed a real-time IoT health monitoring system that can store a patient's basic health parameters for smart cities. Small wearable nonintrusive sensors [23] will facilitate large data to be collected automatically which will reduce regular visits to clinics and hence the expenditure. Future work in this field of research will benefit the entire healthcare domain [24]. A health monitoring system for vital health signs using IoT is an extended technology evolving as an essential system that can be worn for physiological monitoring. Different sensors can be integrated into the wearable and, at the same time, gather bio-signals in a non-invasive way [25,26].

Table 1 presents a summary of related literature on AI/ML applicable to IoHT in healthcare delivery.

Table 1. Summary of related literature on AI/ML applicable to IoHT and vital health signs.

References	Article Type	Taxonomy	Year Covered
Ahmadi et al. [27], 2018	SLR	"Security in IoT e-healthcare based on the cloud storage"	2009–2017
Saheb and Izadi [28], 2019	SLR	"Big data analytics and fog computing in IoHT"	2014–2018
Usak et al. [29], 2020	SLR	"IoT-based healthcare service delivery"	2010–2018
Zou et al. [30], 2020	SLR	"User and data interaction in IoHT"	2018–2019
Sabtos et al. [31], 2020	SLR	"Heart monitoring system using IoT"	2015–2018
Kashani et al. [32], 2021	SLR	"IoT in healthcare"	2015–2020
Kaieski et al. [33], 2020	SLR	Application of AI methods and Vital Signs	2008–2018
Bolhasani et al. [34], 2021	SLR	"Deep learning applications for IoT in healthcare"	2010–2020
Darwish et al. [35], 2017	Survey	"IoT and cloud computing"	Not mentioned
Habibzadeh et al. [36], 2020	Survey	"Healthcare IoT"	Not mentioned
Qadri et al. [37], 2020	Survey	"Emerging technologies in the future of IoHT"	Not mentioned
Kadhim et al. [38], 2020	Survey	"Patient's health monitoring system based on IoT"	Not mentioned
Our Study	SLR	AI-IoT and Vital signs in healthcare	2010–2022

[39] presented a review of smart IoT healthcare. Similarly, [10] investigated the application of wearable body sensors for the analysis and monitoring of physiological parameters based on qualitative synthesis. In another review [31], the work identified, compared methodically, and classified current findings taxonomically in the field of IoHT technology by analyzing several articles within five years. The findings were logical, the approaches to choosing papers were detailed, and the period of coverage was stated. However, an analytical and taxonomy classification of AI/ML and its application in the IoHT for vital health signs was not covered in existing studies mentioned in Table 1. Therefore, this research work explores and investigates the application of AI/ML and IoT for vital health signs in healthcare delivery.

3. Review Method

A systemic review approach was used to minimize bias and to follow a more accurate keyword selection pattern of related research papers. The systemic approach uses some defined search strings to extract closely related articles within the indexed databases.

Conducting the Systematic Literature Review

This phase includes paper selection in two stages; the outcome in "extracted data, and information synthesizing". The selection process commenced with the primary articles. In this stage, the search string (vital signs; healthcare; sensors) + (Internet of Things; artificial intelligence) via Google Scholar as the key search engine by focusing on the indexed academic databases such as: "ACM, Emerald, Hindawi, IEEE, SAGE, Science Direct, Springer, Taylor and Francis, and Wiley". Additionally, the paper selection process is illustrated in Figure 1 as follows.

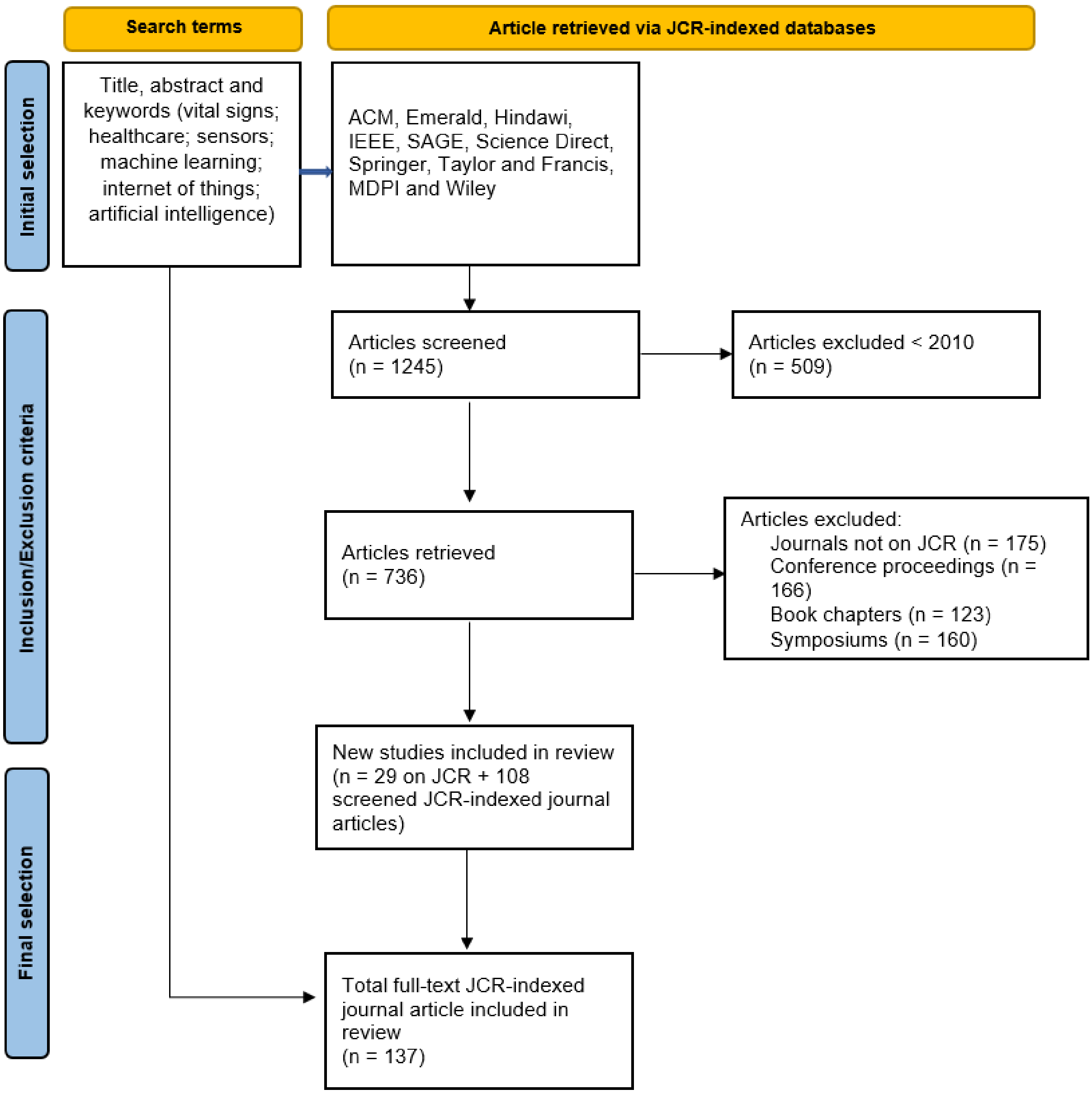

Figure 1. Article selection process.

- Initial selection: This step includes filtering the "titles, abstracts, and keywords of potential primary articles". At this stage, 1245 articles were retrieved, including conference paper proceedings, journal articles, book chapters, books, symposiums, research reports, etc. The search string was applied to address digital databases from 2010 to 2022.
- Final selection: In this step, inclusion/exclusion conditions were used to include important articles and exclude irrelevant ones. In the course of the literature search, a wide range of papers related to the IoT in healthcare delivery were obtained, and regardless of the relevant proceedings and other research reports acquired, only articles found in journal citation reports (JCR) indexed databases were considered based on their full text. At the final selection, 137 JCR-indexed articles were retrieved.

A summary of related articles classified based on disease category (asthma/chronic obstructive pulmonary disease (COPD), cardiovascular diseases, diabetes, and nutrition) and the respective sensor category is presented in Table 2.

Table 2. Summary of related experimental research works on IoHT and Vital Health Signs.

Citation	Article Category	Research Design	No. of Subjects	Sensor Category
Bonnevie et al. [40], 2019	Asthma/COPD	Observational	104	VHS
Caulfield et al. [41], 2014	Asthma/COPD	Observational	10	Physical activity
Naranjo-Hernandez et al. [42], 2018	Asthma/COPD	Observational	2	VHS
Huang et al. [43], 2014	Cardiovascular diseases	Observational	225	Electrocardiogram (ECG)
Javaid et al. [44] 2018	Cardiovascular diseases	Observational	60	Electrocardiogram (ECG)
Dong and Biswas [45], 2017	Diabetes and nutrition	Observational	14	Physical activity, VHS
Alshurafa [46], 2015	Diabetes and nutrition	Observational	10	Physical activity, VHS

According to [19], the IoHT comprises layers of interconnected devices with the ability to exchange and process data to improve patient health. The distinct layers of patient data consist of acquisition (smart health object), storage (personal health record), processing (intelligent algorithms), and presentation (results), as shown in Figure 2.

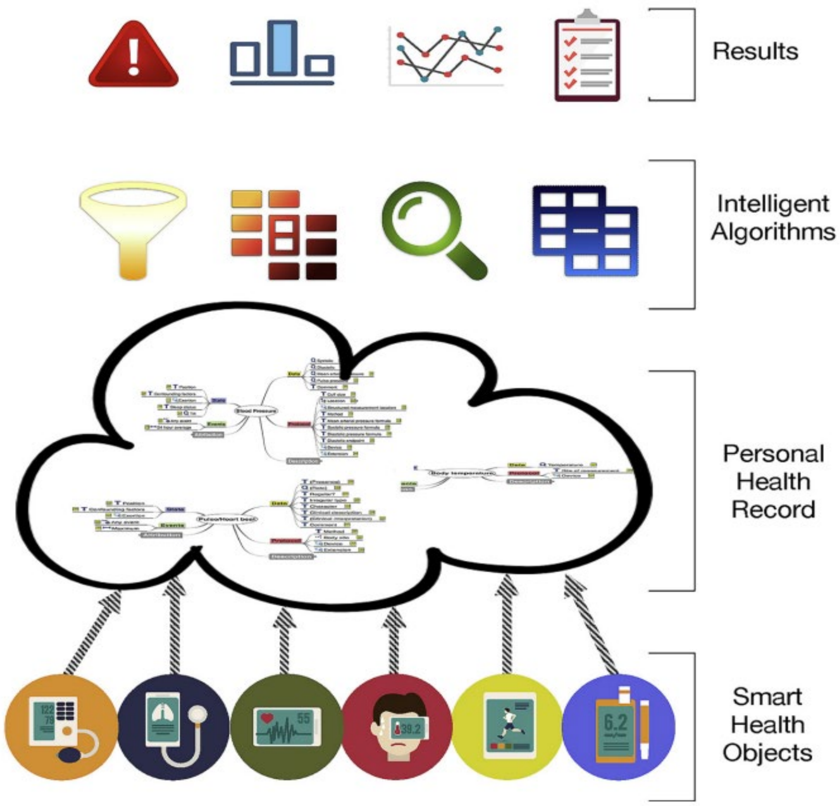

Figure 2. Overview of IoHT patient data layers [19].

4. Internet of Things (IoT) for Healthcare Delivery

4.1. Application of IoT in Healthcare

IoT technology was originally developed in the late 19th century as an interconnected worldwide network, linking sensing, wireless transmission, and information technologies [47]. The IoT has a backbone, known as smart objects, that can transmit and process information with other components of the network. Recently, technology has been developed to define the concept of the IoT, ranging from environmental data analysis to managing telecommunication services, interchanging information, and general applications [48]. The IoT may be interpreted based on contextual purposes, such as "things-centric" (sensors), "internet-centric" (middleware or architecture-oriented), "semantic-centric" (knowledge perspective), and "user-centric" (enabling innovative applications focused on people) [49]. It is also referred to as the interconnection of sensors.

(a) Monitoring of physiological parameters

In recent years, quite a lot of approaches to vital health signs monitoring as key parameters to analyze patient health has been reported. In [50], the system was able to monitor the heart rate and activity recognition using wireless sensor network technology. The system is capable of communicating with medical professionals in the event of anomalies such as falls, tachycardia, or bradycardia through mobile devices. In a similar approach, [51] developed a system for monitoring and tracking patient activities with medical issues. The work of [52] investigates the application of the Blue-mix cloud technique to archive vital signs measured data, enabling remote use by doctors and presenting the vital health sign results via IBM Watson. Similarly, in [53], a real-time IoT-based ECG telemetry system is proposed. The study presented a high-performance quality assessment algorithm implemented on Android mobile devices. The study also showed the effectiveness of the approach under distinct physical actions. Motionless monitoring can influence the use of field sensors that enable the gathering of contextual data for action recognition. An exciting study is proposed in [54] where environmental sensors, an optical-track camera, and smartwatch-embedded IoT-based sensors are used to gather motion, video, and audio signals data conjointly with a specialized wearable for vital parameters measurement.

(b) Rehabilitation systems

The application of protective IoT solutions is efficient in rehabilitation systems where health monitoring is used to detect infections or complicated health challenges, as reported in [55]. The authors proposed a technique to predict the health status of a residual amputee's lower limb by monitoring temperature and gait. The system uses edge devices (Android mobile) to measure and send data to a fog station that implements the ML-based prediction. In a similar approach, [51] proposed a study on the estimation of simplified human limb kinematics based on measurements from two low-power accelerometers placed on the forearm. In the work of [56], the authors describe a voice pathology recognition system that examines data obtained from mobile devices, microphones, and wearable sensors and uses machine cloud-based classification. The work in [57] uses a FOG model to develop a speech recognition ambient assistive system for a patient with Parkinson's health challenges. In their model, the signal is acquired via a smartwatch, followed by feature extraction and model training and classification.

(c) Skin pathologies and dietary assessment

As a result of the recent evolution of mobile deep neural network architectures in industries and homes embedded with pervasive sensors, AI has generated large sets of data that are driving the core of computation and services from the cloud to the edge of the network [58]. Some exciting solutions are beginning to appear in the advanced medical domain. For example, [59] reported results for skin cancer recognition that apply a pre-trained convolutional neural network model running on a smart device and compute a multi-class classification task of skin lesions. In another work, [60] deliberate the importance of FOG-to-Cloud (F2C) that communicates information from patients whose quality of life strongly relies on their motion, such as patients with COPD, to a remote location health facility.

(d) Epidemic diseases treatment and location-aware solutions

The recent COVID-19 pandemic brought new approaches for non-contact measurement of temperature, fever, etc. This resulted in low-cost smart sensors that are environmentally friendly. For example, the AutoTriage system, presented in [61], can run real-time deep learning algorithms at the edge level that identify the forehead and lip regions and permit the temperature estimate of the frontal region of the face with an infrared camera, while cyanosis is detected from lips region in the visible spectrum. In another similar work, [62] proposed a new framework for identifying symptoms of COVID-19 based on smartphone sensors. The framework can be used by both experts (radiologists) and non-experts on smartphone devices for malware detection purposes.

In general, IoT-based health monitoring is gradually being widely accepted by medical practitioners in the areas of real-time medication and rehabilitation. In related work, the relationship between edge and cloud computing was presented in [63]. In the reported work, a COPD patient used a portable oxygen concentrator (POC) with an IoT device to transmit information aimed at adjusting and tailoring the oxygen concentration to the patient's real-time situation. This safeguards a therapy tuned to patients' activity by constantly collecting and processing health-related information.

(e) Diabetes treatment

Recently, an increasing number of smart sensor solutions have been used in diabetes treatment. Many wearable and mobile monitoring devices such as blood glucose monitors, insulin pens, insulin pumps, and closed-loop artificial pancreas systems are capable of wireless transmission, with smartphones or tablet devices providing simple analytic services without cloud support, as reported in [64]. Additional contributions in this area focused more on model interpretation to predict the onset of the disease. For instance, [65] proposes a decision support system for diabetes prediction based on ML techniques and compares handcrafted machine learning with deep learning approaches. Finally, a deep learning model to predict diabetes, stress types, and hypertension attacks from wearable smart devices is discussed in [66], where the authors implemented a FOG-based deep learning model (DeepFog) that collects data from patients and classifies their wellness state using a robust multi-dimensional data deep neural network model.

4.2. Communication Technologies for IoT in Healthcare

Several wireless technologies have been applied in the interconnection of IoHT systems, as presented in Table 3. The present protocols mostly used for mapping the IoHT devices are, according to [19], wireless fidelity WiFi (use in local area networks), worldwide interoperability for microwave access WiMax (use in broadband wireless networks) global system for mobile communications (GSM) and enhanced data rates for GSM evolution (EDGE) for 2nd generation (2G) mobile carriers networks, universal mobile telecommunications system (UMTS) and code division multiple access (CDMA) for 3rd generation (3G) telecommunication, and long-term evolution (LTE) for 4th generation (4G) mobile telephony [67]. Personal area networks (PAN) are generally applied in the development of IoHT. A wireless personal area network (WPAN) is regarded as a low-powered PAN for a close-range wireless network and includes technologies such as infrared (i.e., wireless optical communication based on the point-and-shoot principle), ZigBee (which provides a low-energy consumption, but also low transmission rates [68]), ultra-wideband (UWB) 3-D tracking of multiple tags for clinical usage [69] and Bluetooth and Bluetooth Low Energy (BLE) [70]. Another choice for communication in the IoHT is the application of protocols that are based on electromagnetic field communications, comprising radio-frequency identification (RFID) based solutions to tracking patient movement and location [71] and near field communication (NFC) [72].

The unique ideology of the IoT is precisely linked to the radio frequency identification concept, which usually comprises the tags and readers for data acquisition. These are mostly used in the field of logistics [47]. The tags and readers of radio frequency identification can be either passive or active. The active component possesses an internal power source that enables wider spectrum communications and supports the passive component of the device [48]. Recently, the application of radio frequency identification in physiological parameter estimation has been considered a novel approach. This is true because of the advent of ultra-high frequency readers with advanced sensing features. This also allows a more friendly and easy approach to sending patient data across the IoT chain. Near-field communication is a non-invasive concept of communication that can detect vital signs within a short range [73]. In addition, near-field communication has proximity features with simple handling mechanisms. Thus, communication within the hospital records becomes easier. Low power area networks (6LoWPAN) permit the Internet Protocol Version 6 (IPv6) layer to be conveyed on the WSNs to the range of a sensor node with the IoT platform [74]. Internet Protocol Version 6 presents several merits to the IoHT technology, comprising better scale, optimizing mobility, efficient management, and permitting enhanced smart object regulations.

Table 3. Overview of interconnection technologies commonly used in IoHT devices, partially obtained from [19,47,48,73,74].

Interconnection Protocol	Range	Data Rate	Spectrum
WiFi	200–100 m	50–90 Mbps	2.4/5 GHz
WiMax	50 Km	10–376 Mbps	2–11 GHz
GSM/EDGE	<35 Km	270 kbps	900–1800 MHz
UMTS/CDMA	<30 Km	2 Mbps	1885–2200 MHz
LTE	<100 Km	<300 Mbps	700–2500 MHz
Infrared	1–10 m	2.4 kbps–1 Gbps	300 GHz-430 THz
ZigBee	10–20 m	20–256 kbps	2.4 GHz/84–915 MHz
UWB	2–30 m	110 Mbps	>500 MHz
Bluetooth	<100 m	2.1 Mbps	2.4 GHz
BLE	<50 m	1 Mbps	2.4 GHz
NFC	<10 cm	106–424 kbps	13.56 MHz
RFID	5 cm–2 m	40–640 kbps	120–150 kHz
NFC	<10 cm	106–424 kbps	13.56 MHz
6LoWPAN	<50 m	250 kbps	868 Hz/902 MHz/2.4 GHz

4.3. IoT and Vital Health Signs Monitoring

The IoHT is useful in analyzing physiological signs and related clinical data. Traditionally in hospitals, vital sign data are usually acquired manually. For example, analogue devices such as sphygmomanometers, stethoscopes, or interviews are commonly used in determining the degree of pain. However, using digital and smart AI devices makes data acquisition and analysis much easier for medical doctors. In addition, the chances of errors occurring as a result of human intervention and manual annotation would be reduced to a minimal level [75].

Recently, wearable technology and wireless sensors sensor networks were used in the acquisition of vital signs, as reported in [76]. For more efficient data acquisition, vital health signs and interconnection of IoT devices should be an IP-based protocol instead of the manufacturer standard, for instance, IPv6 instead of 6LoWPAN [77]. Analysis of the state of body pain using smart sensors, location, and accelerator for activity and speech recognition was proposed in [78]. The authors claimed that data from facial expressions were collected and analyzed using image processing. In monitoring the state of consciousness, the facial expression data combined with the speech audio signals were used.

5. Artificial Intelligence (AI) for Healthcare Delivery

5.1. Application of AI in Vital Health Signs Monitoring

(a) Diagnosis

Diagnosis is the identification of the nature of an illness or other problem by examination of the symptoms with the aid of clinical devices. For instance, the excessive rate of occurrences of heart disease has resulted in the development of smart devices and systems that can detect/recognize early warning symptoms of anomalies. More recent findings have shown that heart diseases are the topmost leading cause of death; thus, we need to detect symptoms of these diseases before they get worse [79]. A non-contact HR measuring device was proposed that operates based on a sparse reconstruction algorithm via a smartphone video camera. The integration of AI, IoT, and vital signs into a single platform has demonstrated a remarkable way to monitor patients' health and diagnose anomalies. The most commonly used devices in clinics are ECG, pulse oximeter, wearable wristwatches, and BT sensors. ECG signals represent the electrical activity of the heart at rest. It can be used to create conclusions about heart rate activity and can be applied for diagnosing the enlargement of the heart due to high blood pressure, elevated heart rate, and dysrhythmia or heart attacks [80]. Gupta et al. [81] proposed an AI-based model to diagnose heart diseases by monitoring several parameters in real-time, using wearable IoT technology. According to their findings, wearable ECG devices, pulse, and temperature sensors with a trained prediction model were used to classify risk for heart disease or arrhythmia.

(b) Prognosis and spread control

Recently, the IoT or IoMT has been regarded as an emergent technology in the field of vital signs prognosis and disease spread control. Healthcare is a significant field, and the recent integration of A-IoT has created more opportunities for proper health monitoring. The IoT has been used by researchers all over the world to develop systems for monitoring, detecting, preventing, and controlling the spread of various diseases. In another recent study, the IoT was deployed in active and assisted living (AAL) research and development to support elderly people suffering from memory impairment in their daily activities [82]. According to the report, "the model is implemented as an extension of the human behaviour monitoring and Support (HBMS) approach that provides a conceptual "human cognitive model" for representing the user's behaviour and its context in her/his living environment. The prevention of the occurrence of a pandemic outbreak involves prompt diagnosis. Pulmonary infections like the influenza virus have a long history of quickly turning into pandemics, with the most recent worldwide pandemic also being one that affects the respiratory system—the COVID-19 pandemic. Therefore, it is required that there is a system in place to identify and predict the occurrence of such diseases that might cause outbreaks before they take effect since it is easier to control these diseases at an early stage than when they start spreading rapidly.

(c) Assistive systems

According to [83], assistive systems are systems that act as rehabilitative frameworks that provide support in daily life for people with disabilities. These form an important class of applications for ML-based IoT. Most of the modern motorized prostheses are controlled with surface electromyography (SEMG) recorded on the residual muscles of amputated limbs. However, the residual muscles are usually limited, especially after above-elbow amputations, which would not provide enough SEMG for the control of prostheses with multiple degrees of freedom. Signal fusion is a possible approach to solve the problem of insufficient control commands, where some non-EMG signals are combined with SEMG signals to provide sufficient information for motion intension decoding". The study in [83] proposed a motion classification method that combines SEMG and electroencephalography (EEG) signals to improve the control performance of upper-limb prostheses.

(d) Monitoring

Another important aspect of vital signs analysis is monitoring. According to [84], "the continuous monitoring of a person's health is gaining a lot of recognition since it can not only drastically reduce the mortality resulting from sudden emergencies, but also promote awareness about one's health and hence lead to a healthier lifestyle. Farhan et al. [84] propose a novel feature set for continuous, real-time identification of abnormal BP. This feature set is obtained by identifying the peaks and valleys in a PPG signal (using a peak detection algorithm), followed by the calculation of rising time, falling time, and peak-to-peak distance. The histograms of these times are calculated to form a feature set that can be used for the classification of PPG signals into one of two classes: normal or abnormal

BP. Apart from being able to analyze the raw clinical data, IoT can help doctors monitor the physical activities of patients. For instance, the SPO2 concentration, heart rate, and temperature of a person were monitored, as presented in [85].

5.2. Intelligent Algorithms for Vital Signs Monitoring

Different machine learning and data analysis methods proposed in many studies can be applied to physiological signs. For instance, linear support vector machines (SVM) reported in [86] were successfully applied in the analysis and classification of physiological parameters such as BP, HR, SPO2, glucose level, etc. Supervised ML classifiers such as decision trees (DT), Naïve Bayes (NB), linear regression (LR), random forest (RF), support vector machine (SVM), and k nearest neighbour (KNN) were the most used approaches for disease detection, recognition, and classification [87]. Moreover, classes of artificial neural networks (ANN) classified has also been used in health-related areas. The earliest studies in the field of ANN include long short-term memory (LTSM) and recurrent neural networks (RNN), as reported in [88]. Table 4 presents a summary of the AI methods used in vital signs diagnosis.

Table 4. AI/ML methodology for IoT and vital signs diagnosis.

Citation	AI/ML Methods	Application	Description	Function
Michalski et al. [89], 2019	"RF/SVM"	"Heart disease diagnosis"	"Creation of classification and regression analysis"	"Develop a hyperplane. Use in pattern analysis puzzles and nonlinear regression"
Martis et al. [90], 2018	"NB"	"Heart disease diagnosis"	"Probabilistic classifiers"	"Creation of classification, sentiment analysis, spam filtering, and news classification"
Guan et al. [91], 2019	"Cluster analysis and efficient differentially private data clustering scheme"	"Heart disease diagnosis"	"Classify a sample of subjects (or objects) based on a set of measured variables in different groups"	"Interaction using the K-means algorithm"
Attia et al. [92], 2019	"Convolutional neural network (CNN)"	"Heart disease diagnosis"	"Class of deep neural network (DNNs), most commonly applied to analyse visual imagery. Known as shift invariant or space invariant artificial neural networks (SIANN)"	"Classify patients with ventricular dysfunction"
Wu et. al. [93], 2019	"DL"	"Heart disease diagnosis"	"DNN learning and a prediction mode"	"Enable machines to process data with a nonlinear approach"
Kumar et al. [94], 2018	"Recurrent fuzzy neural network"	"Heart disease diagnosis"	"Neural Classifier"	"Using DPSS to help prevention healthcare services and data security"
Heidari et al. [95], 2019	"Grasshopper optimization"	"Heart disease diagnosis"	"Gravity force and the wind advection AI"	"Multi-linear perceptron (MLP) ANN for tackling optimization with flexible and adaptive searching methodology"
Li et. al. [96], 2019	"ReliefF and RS"	"Heart disease diagnosis"	"Approach as an integrated feature selection system for heart disease diagnosis"	"To data analysis and data mining that has been applied successfully to many real-life problems in medicine, pharmacology"

Table 4. *Cont.*

Citation	AI/ML Methods	Application	Description	Function
Heidari et al. [95], 2019	"Multilayer perceptron (MLP)"	"Heart disease diagnosis"	"MLP and ANNs technology together"	"Provide various continuous functions"
Fki et al. [97], 2018	"KNN, NB, SVM, LR, support vector regression, classification trees, regression trees, and RF"	"Prediction outpatient treatment"	"ML with IoT data for risk prediction"	"The model is a set of hypotheses about dialysis biomarkers proved in a probabilistic format"
Ghazal et al. [98], 2021	"Supervised Learning, Unsupervised Learning and Reinforcement Learning"	"Prediction outpatient treatment"	"Classifications and Prediction models"	"Provides different procedures used in all the three learning styles"
Yao et al. [99], 2019	"CNN"	"Prediction outpatient treatment"	"Deep learning model for predicting chemical composition"	"Developed CNN, like stacked auto-encoders, deep belief networks, and RNN"
Troisi et al. [100], 2019	"TORS"	"Robot surgery"	"Transoral Robotic Surgery"	"Fewer blood losses, faster postoperative recovery, and fewer adhesions"
De Momi et. al. [101], 2010	"AESOP"	"Robot surgery"	Automatic Endoscopic System for Optimal Positioning	"Robotic endoscope and surgical robotic systems"
Panesar et. al. [102], 2019	"STAR"	"Robot surgery"	"Smart Tissue Autonomous Robot"	"Nascent clinical viability of a self-governing soft-tissue surgical robot"
Chen et. al. [103], 2018	"5G-Smart Diabetes"	"Personalized healthcare"	"Personalized diabetes diagnosis"	"Real-time system to analysis diabetes suffering"
Katzman et. al. [104], 2018	"DeepSurv"	"Personalized healthcare"	"DNN and state-of-the-art survival method"	"Provide individual treatment recommendations"
Nayyar et. al. [105], 2019	"BioSenHealth 1.0"	"Personalized healthcare"	"Real-time monitoring of vital statistics of patients"	"Live data access using thingspeak.com cloud platform"

Recently, an automated computerized tomography (CT) quantification of epicardial adipose tissue using the deep neural network (DNN) approach was presented in [106]. In this study, a fully automated deep convolutional neural network (CNN) method was trained to predict EAT on non-contrast material-enhanced calcium-scoring CT scans from multiple cohorts, scanners, and protocols. According to [89], RF outperformed the state-of-the-art ML algorithm used on clinical data. Another closely related review on ML with WSN in smart healthcare was presented in [98]; the study presented different categories of AI-powered WSNs and IoT used in the healthcare domain. [107] presented a comprehensive review of the ML techniques used in healthcare systems.

Furthermore, a class of RNNs known as gated recurrent units was used to develop a DL model, as reported in [99]. The authors' novel contribution has led to broader research dimensions in the area of clinical data analysis. Recently, another class of supervised DNN, called CNN in [98,100], has been used in medical data analysis and classifications. The CNN is a class of the ANN that is made up of thousands of neurons and hidden layers. It is mostly applied to visual imagery (medical images and vital signs). It is considered end-to-end automated learning as it does not involve human intervention [108–110].

Several researchers in the area of cardiovascular monitoring in the healthcare system have explored AI, in particular, ML algorithms [111–115]. The most common ML techniques used in heart disease diagnosis are SVM and NB. According to [101], SVM and NB ML methods are used in heart disease diagnosis systems. The SVM develops a set of hyperplanes in the infinite-dimensional area. It estimates the linear separation surface with a maximum margin in a provided training dataset. Also, SVM has been widely used in pattern analysis puzzles and nonlinear regression. However, it does not make any strong hypotheses about the data [116–119]. The NB method is mostly used in text recognition, classifications, and spam filtering [120–122]. The NB performs well if the input data are arranged in distinct groups and requires less data than other ML approaches [102].

Moreover, there is a need for a mobile heart rate monitoring system for "atrial fibrillation detection". The mobile system achieved real-time "arrhythmia detection". In addition to conventional wearable healthcare devices, ML models can be applied to more efficient approaches to HR diagnosis via remote patient monitoring [92]. According to the study in [43], "ML models can predict the possibility of an occurrence of a heart attack in the nearest future. At the Mayo Clinic, researchers examined the heart's electrical activity using AI with ECG signals and identify asymptomatic left ventricular dysfunction (ALVD). The research shows that using the ECG data, CNN works on classify ejection fraction $\leq$35% for patients with ventricular dysfunction [92]. The results showed that AI applications using ECG data are a low-cost approach that allows identifying ALVD in asymptomatic individuals easily".

5.3. AI/ML Models Taxonomy Used in Healthcare Systems

This section explains the application of AI/ML algorithms used in healthcare systems. AI is regarded as a broad family name that comprises ML reinforcement learning (RL), and DL as shown in Figure 3. AI "is the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages" [123]. ML is "the use and development of computer systems that can learn and adapt without following explicit instructions, by using algorithms and statistical models to analyze and draw inferences from patterns in data" [124]. ML is categorized into supervised learning (SL), unsupervised learning (UL), and semi-supervised learning (SSL) [125]. In SL, the algorithm learns from a labelled training dataset and makes predictions that are compared with the actual output values. If the predictions are not correct, then the algorithm is modified until it is satisfactory. This learning process continues until the algorithm achieves the required level of performance; examples of SL algorithms are SVM, NB, LR, etc. [126–128]. The UL algorithm does not require labelled data to learn and create a model. The algorithm is left unsupervised to find the underlying structure in the data to learn more and more about the data itself; examples of UL algorithms are k-means clustering and apriori algorithms (associations) [129,130]. The SSL is a combination of supervised and unsupervised machine learning that uses a small amount of labelled data like SL and a larger amount of unlabelled data like UL to train the algorithms. First, the labelled data is used to partially train the machine learning algorithm, and then this partially trained model is used to pseudo-label the rest of the unlabeled data. Finally, the ML algorithm is fully trained using a combination of labelled and pseudo-labelled data [124]. Reinforcement learning algorithms (RL) learn optimal actions through trial and error. This means that the algorithm decides the next action by learning behaviours that are based on its current state and that will maximize the reward in the future. This is done using reward feedback that allows the RL algorithm to learn which are the best behaviours that lead to maximum reward. This reward feedback is known as a reinforcement signal [131–134]. The DL is a subset of the AI family. It is based on learning by example, just like humans, using artificial neural networks. These ANNs are created to mimic the neurons in the human brain so that DL algorithms can learn much more efficiently; examples of DL algorithms used in healthcare systems are CNN, RNN, deep belief networks (DBN), recurrent CNN (R-CNN), etc. Moreover, cascading the DL and RL algorithms result in enhanced performance algorithms such as Deep Q-Networks (DQN) [123].

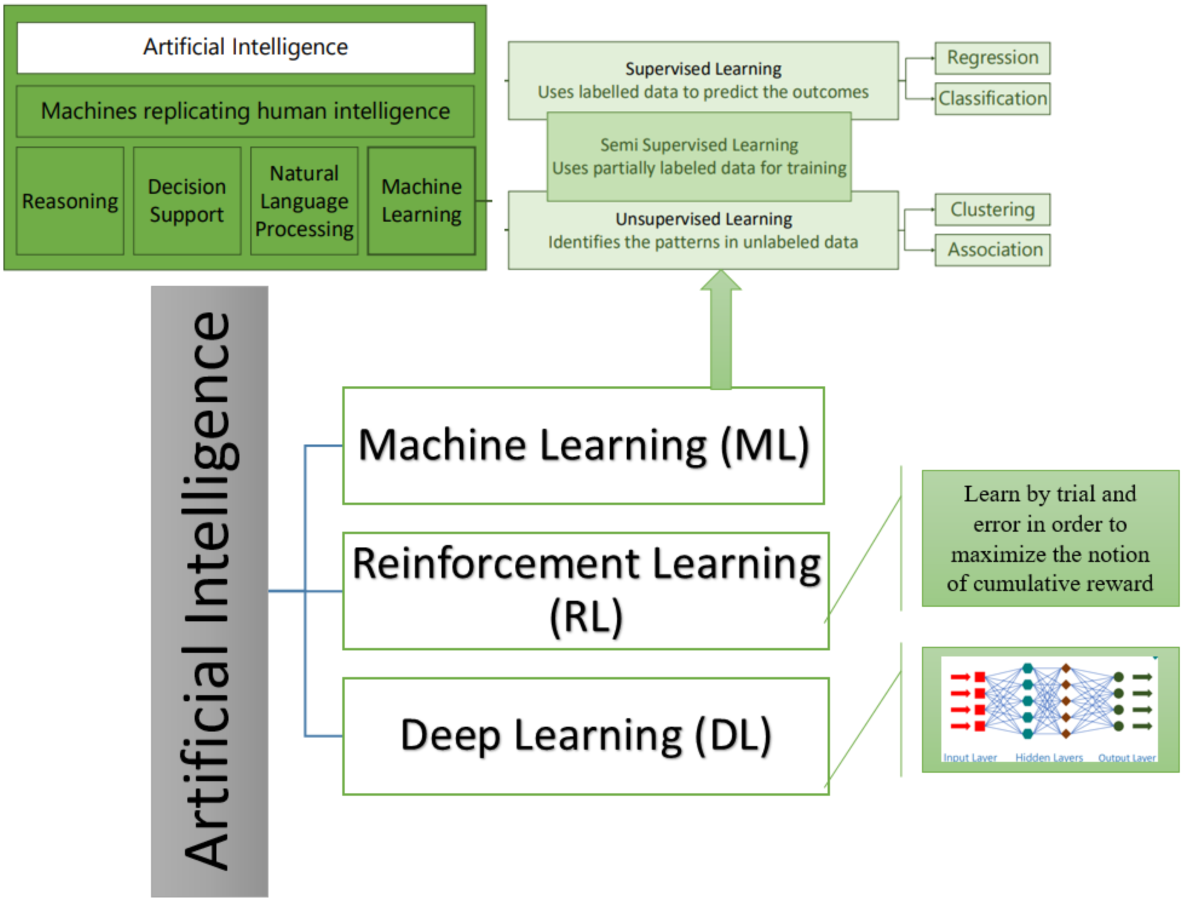

Figure 3. A depiction of AI, ML, RL, and DL methods used in healthcare systems.

The IoHT and personalized healthcare systems can be seen as the global support of the data collected from medical devices. According to Oniani et al. [39], "It is a large area that includes the blockchain for IoMT in medicine, wearable sensors, mHealth Things, IoT networks for healthcare, Big Data, ambient sensors, MEMS devices, robotics in the healthcare industry, mobile health systems, health informatics security, privacy methods, and AI. Regarding heart disease diagnosis, the primary usage of ML algorithms is the supervised learning models such as (NB, SVM, and MLP), and unsupervised such as (cluster analysis, and private data clustering schemes). In the predictive methods, the most used methods are CNN and KNN as presented in Figure 4. Besides, robotic surgery systems are relevant to support health professionals. Nevertheless, the non-autonomous technologies such as TORS and AESOP lead to several advantages as these methods provide less aggressive treatments and provide better results in terms of blood loss and a faster recovery".

5.4. Technical Challenges of AI/ML in Healthcare Delivery

The AI models have presented reliable results in healthcare systems; however, some technical challenges exist. The ML approaches depend greatly on the availability of large vital signs data needed for model training. These data may contain artefacts or bias at sources of acquisition which may lead to over-fitting/under-fitting of the trained model. In addition, if there is an inadequate inter-expert agreement, it has been proven that consent diagnosis and monitoring significantly increase the prediction/classification results of ML models. Correspondingly, for ML applications, the clinical data on patients' medical health status need to be annotated by clinicians and stored efficiently [135–137]. This stage of data analysis is considered excessively expensive, especially on a large data scale. "This implies that larger-scale data-collection and data-annotation efforts are needed to develop higher performance end-to-end AI clinical systems”.

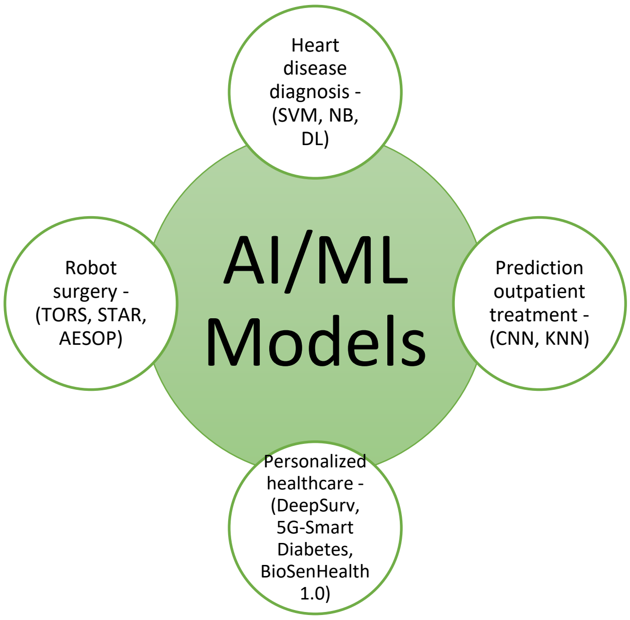

Figure 4. AI/ML algorithms and their application areas in healthcare.

Similarly, numerous highly efficient ML models produce outcomes that are challenging to interpret and analyze by non-experts. Even though such AI/ML models achieved higher performance than even humans on conventional datasets, according to [110], it is not straightforward to convey intuitive notions explaining the conclusions of the models, identify model weaknesses, or extract additional biological insights from these computational black boxes. Recent approaches to explain image classification models include visualizing the convolution filters or the relevance of each image region using saliency maps. However, model interpretation remains much more challenging for DNN models trained on data other than images”.

6. Discussion and Future Research Directions

In the IoHT layers presented in Section 2, the physiological data acquired are transmitted to the PHR layer (cloud storage), then the intelligent layer, and the result presentation layer. According to [101], a different approach for the analysis of clinical data in the cloud was proposed. In the area of FOG, clinical data can be collected and analyzed with available distributed edge resources easily by linking isolated cloud resources. The author in [102] observed the challenges between load balancing and remote resources edge capability. The PHR commonly used in medical/health environments may need more experts to operate/handle them as it involves a lot of information transfer across platforms, as reported in [92,103]. Better feature analysis and representation is necessary across the IoHT chain for more enhanced processing of data by the computers. The PHR is considered the best option for data representation using the concept of web semantic ontologies, as reported in [92]. However, PHR faced a few challenges, particularly during the interconnection of wearable sensors with clinical vital health data. Similarly, the increase in the data flow (big data) and acquisition complexity may create difficulties in the analysis of clinical information by doctors. As such, the need for an advanced machine learning approach (AI) in the analysis and better interoperability of clinical vital signs cannot be overemphasized.

Shallow data mining approaches such as DT, LR, RF, KNN, SVM, and ANN were used to compare intensive care unit mortality prediction models [104]. The authors ranked and compared the classification algorithms by fine-tuning their hyper-parameters for the best model fit. For instance, the physiological vital signs parameters, heart rate, blood glucose level, body temperature, blood pressure, oxygen saturation, etc., were measured and analyzed using a decision tree classifier. The increase in interconnections and data exchange among IoT devices has led to the era of "data-hungry traditional ML methods" [105] and the advanced ML approach (DL). Despite the performance of deep learning models on a large volume of data, the results obtained sometimes face interpretation challenges. For instance, a researcher must identify the performance evaluation metrics (confusion matrix) suitable for the interpretation of associated hyper-parameters. This led to more findings in the field of DL for better results analysis and presentation [106].

Future research in the area of AI, IoT, and vital health signs can focus more on the Blockchain, tactile internet, online social networks, big data analytics, virtual reality, augmented reality, and the internet of nano things. Furthermore, as the number of wearable sensor production is increasing, there is a need for quality control and standard regulations to ensure interoperability and standardization of interfaces and protocols, which is missing in state-of-the-art health IoT devices. The lack of non-uniformity and communication between the sensors and the vital signs is regarded as the main challenge in AI/IoT integration. Similarly, there is a need to optimize security and minimize device power dissipation, computational complexity, and memory issues. Therefore, the integrated IoT health monitoring system can be optimized in real-time with proper encryption and an uninterrupted power supply.

7. Conclusions

This paper has extensively reviewed the existing research articles, compared them systematically, and classified current findings taxonomically in the field of IoHT technology by analyzing several articles within the last decade (2010–2022). The paper focused on monitoring and identifying physiological parameters (vital signs) acquired using wearable sensors (IoT) and AI for clinical health-related findings.

The paper started with a general overview of AI, IoT, vital signs, and related experimental research works. According to the review findings, vital signs commonly monitored and measured in clinical environments include heart rate, blood pressure, respiratory rate, oxygen saturation, body temperature, and glucose level. These physiological parameters are measured based on traditional approaches, mainly heuristics, and sometimes have a high level of errors.

Another contribution of the study constitutes the application of the IoT in healthcare, including monitoring physiological parameters, rehabilitation systems, skin pathologies, diabetes, and epidemic disease treatment. Since data are mostly acquired using smart health objects (SHO) and transit to the personal health record layer (storage), there is a need for better intelligent algorithms for enhanced analysis and interpretation of results for health givers and healthcare providers. Vital signs are collected via wearable (SHO) and transmitted clinical information to the cloud via communication protocols on devices such as WiFi, WiMax, ZigBee, Bluetooth, NFC, RFID, or UWB, as summarized in Section 4.2.

In addition, the commonly used AI techniques in vital health signs analysis such as the ML, DL, and RL algorithms were discussed. Finally, application areas of AI models in vital health signs monitoring were discussed, starting with diagnosis, prognosis and spread control, assistive systems, prediction, heart disease diagnosis, robot surgery, personalized healthcare, and monitoring.

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