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Online heart monitoring systems on the internet of health things environments: A survey, a reference model and an outlook

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ABSTRACT

The Internet of Health Things promotes personalized and higher standards of care. Its application is diverse and attracts the attention of a substantial section of the scientific community. This approach has also been applied by people looking to enhance quality of life by using this technology. In this paper, we perform a survey that aims to present and analyze the advances of the latest studies based on medical care and assisted environment. We focus on articles for online monitoring, detection, and support of the diagnosis of cardiovascular diseases. Our research covers published manuscripts in scientific journals and recognized conferences since the year 2015. Also, we present a reference model based on the evaluation of the resources used from the selected studies. Finally, our proposal aims to help future enthusiasts to discover and enumerate the required factors for the development of a prototype for online heart monitoring purposes.

1. Introduction

Recently, cardiovascular diseases (CVD) have become the leading cause of death in the world, accounting for about 17.7 million, or 31%, of all deaths in 2017 [1]. CVDs are associated with disorders of the heart and blood vessels which might often lead to cardiac arrhythmia, stroke, hypertension, and heart failure. CVDs are classified as chronic non-communicable diseases (NCD) which also include cancer, diabetes, and chronic respiratory diseases, for example [2]. NCDs are associated with a slow, long-term, or even lifelong advancement, and are usually silent or symptomatic, thereby affecting the quality of life [3].

Several factors contribute to the development of CVDs, but poor lifestyle management such as inadequate diet, sedentary lifestyle, stress, and legal and illicit drug use are determining factors for the progression of these pathologies [4]. Therefore, proper care can significantly reduce the likelihood of heart problems as well as routine examinations and follow-ups by a cardiologist as treatment expenditures become excessive when cardiovascular risk factors are poorly controlled.

The electrocardiogram (ECG), even with more than one hundred years of use, is still the first non-invasive test used for the diagnosis of CVDs and should be interpreted according to the clinical information obtained during the anamnesis and physical examination. The ECG can be recorded at rest and during work (ergometric test) as the patient might have a resting ECG without changes, but when submitted to stress, significant changes might occur [5]. Similar to the ECG, the Holter monitor also records the electrical signals of the heart. The difference is that the handheld device monitors continuously for 24 hours or more, and thus, it detects cardiac arrhythmias that might occur at varying times during the stipulated period of the examination. Moreover, in the case of diseases already diagnosed, it can evaluate the effect of the treatment.

In this context, computational techniques can be used as complementary alternatives to conventional approaches. These methods analyze data or clinical treatments related to a cardiac evaluation faster and more accurately. Among these techniques, we can highlight the following: Feature Extraction [6,7], Image Analysis and Image

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Processing [8,9], Signal Analysis and Signal Processing [10], and Prediction [11,12]. Another recent approach used for monitoring and information management is the Internet of Things (IoT), which involves storing and transmitting real-time information from a physical network by using specific sensors. Furthermore, in its application in the field of health, IoT is referred to as the Internet of Health Things (IoHT). It is a rapidly progressing field with various investments related to improvement and use from IoT. It is estimated that in 2020, IoHT will have an economic impact of US $170 billion according to the McKinsey study [13]. IoHT can contribute to the expansion of access to quality health through dynamic monitoring of the human being within his/her environment. In this way, IoHT can improve the effectiveness of the treatments, prevent risk situations, and assist the promotion of good health. Furthermore, IoHT enhances the efficiency of resource management through flexibility and mobility using intelligent solutions. However, this requires a transition from clinical-centered treatment to patient-centered medical care such that each agent, such as the hospital, the patients, and services, are perfectly connected [14].

Researchers and institutions are dedicated to the development of IoT-based technologies for health applications. Researches such as [15–21] discuss various services, applications, and systems that have been developed based on wearable medical sensors (WMS), illustrating their objectives and challenges. The differential of this survey is to present and analyze the advances of recent studies in health systems based on IoT, focusing on solutions for monitoring, detection, and support of the diagnosis of CVDs by capturing and processing biosignals generated by the human body.

We can summarize contributions that this survey covers from the literature of the last three years in the field. Our research provides a more detailed account of the most widely used and relevant protocols and standards compared to other research papers in the field. Moreover, our work provides extensive knowledge about how security issues are being addressed in the projects selected for analysis. Furthermore, we present how this information can be used for companies that want to explore the currently underdeveloped market for IoT solutions for health. To determine whether electrocardiography (ECG) or photoplethysmography (PPG) is the best technology for the development of its application, we present a study evaluating the respective points assessed in the works on the selected technology.

Another essential point that describes this work is that it is a potential reference material for all professionals involved in the health sector, such as physicians, nurses, physical therapists, and physical educators. They need to know about the models and metrics for adopting the proposed solutions in patients associated with cardiovascular diseases. Currently, there are not sufficient number of articles devoted exclusively to presenting evaluations of the studies on the use of IoHT to validate the diagnosis and monitoring of CVDs; this indicates the valuable contribution of this work. This study would aid any health care enthusiast interested in the use of IoT solutions in the collection, decision support, and monitoring of the cardiac factors develop a systemic view on this subject. Finally, the manuscript presents a reference model aimed at helping future enthusiasts discover and subsequently enumerate the factors necessary for the development of a prototype for online heart monitoring purposes.

The rest of this research is structured as follows: In Section 2, we present the methodology of this survey, focusing on the research questions, search process, inclusion and exclusion criteria, quality evaluation, and data collection. Section 3 describes the results of using the proposed method, analyzing and subsequently citing the relevant studies with a description of the topic interlinked with the research. In Section 4, we present a discussion highlighting certain challenges still to be overcome, and later, we present a model that can be adopted in projects involving the development of experiments related to the IoT for heart monitoring. Finally, in Section 5, open questions and future directions regarding the internet field of things of the heart are provided. Moreover, we have summarized the implications of this survey.

2. Methodology

The methodology adopted to conduct this survey is based on three stages: (1) To develop research terms related to CVDs and the IoT. The primary objective was to obtain the most significant number of researches of these specific applications addressed in our study. Therefore, the search string defined was: ("Internet of Things" or "IoT") and the term associated with cardiovascular diseases. The expressions used in this research related to CVDs are Heart, Cardiac, Electrocardiogram, Blood Pressure, Cardiovascular, Beats, Arrhythmia, Electrocardiography, Cardiology, HRV, Hypertension, Coronary, Myocardial, and CVD. (2) The expressions were adapted to the search engines according to the rules defined by each database and by filtering the search only by magazines and congresses. For the articles we find two or more expressions of, we attempt to exclude the same articles that generated duplicity. (3) Apply inclusion criteria: Works related to wearable technologies that focus on using IoT to improve the prognosis or possible decision support based on the capture and processing of bio-signals generated by the human body by monitoring heart rate and blood pressure.

This survey includes works published since 2015, given that we intend to find the most recent research on the development of health applications for CVDs based on the IoT infrastructure. The selection of the studies was made in the bases of IEEEXplore, Springer, Science Direct, SAGE, PLOS, MDPI, Inderscience Online, Hindawi, Frontiers, and ACM. Other publications that were not associated with one of the mentioned databases were selected using Google Scholar.

Finally, we obtained a total of 115 works, 55 from IEEEXplore, 19 from Springer, 9 from ScienceDirect, 6 from MDPI, 3 from ACM, 3 from PLOS, 1 from Frontiers, 1 from Hindawi, 1 from Inderscience, 1 from SAGE, and 16 other papers were selected due to their content being necessary for the presentation of this research work.

3. Online cardiac monitoring

This paper presents IoT-based cardiovascular health research of the last four years and uncovers numerous issues required to be addressed to transform heart health care technologies through IoT innovation. As mentioned in Section 2, the relevant work is divided into different groups or categories, which represent the researchers' focus in addressing the potential of IoT in the field of heart health, considering several practical challenges. Therefore, there are now several applications, services, processes and prototypes in the field of our research. The research trends we found are represented in Fig. 1 and have been discussed in the following subsections. General observations, including computational resources used in prototypes, are discussed in Section 4.

3.1. Monitoring signals to the heart

Making a medical diagnosis is an imperfect process based more on probability than on certainty. According to Sackett et al. [22], "Evidence-based medicine is the conscious, explicit, and judicious use of the best available evidence that is capable of justifying decision-making by caring for individual patients". Diagnostic tests are important tools to facilitate the health professionals' decisions regarding the treatment that will be administered to the patient. In the face of a list of symptoms and signs, some diagnostic hypotheses get delineated in the mind of the health professional.

3.1.1. Heart Rate (HR)

Heart rate refers to the number of times a person's heart beats per minute. The normal heart rate varies from person to person, but the normal range for adults is 60 to 100 beats per minute (BPM) [5]. However, a normal heart rate depends on the individual's age, body size, heart conditions, whether the person is sitting or moving, and the use of medication; even physical conditioning reduces the overall resting heart rate, making the heart muscles work more efficiently.

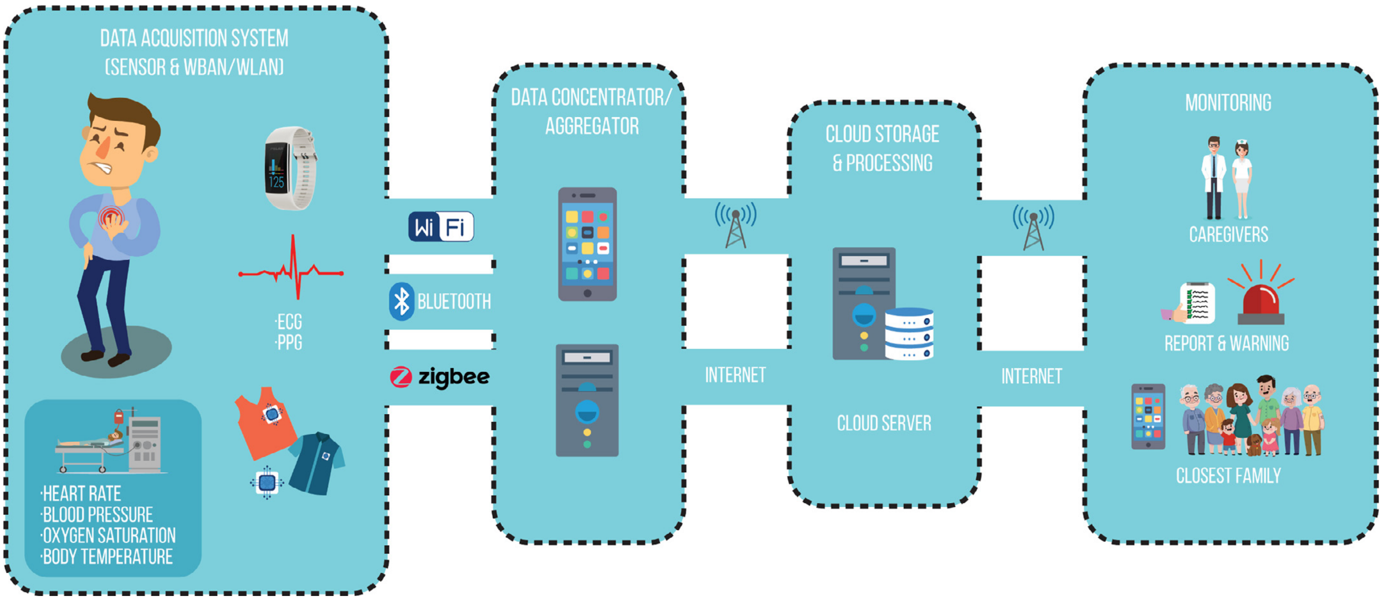

Fig. 1. IoT of the Heart.

An arrhythmia causes the heart to beat too quickly, too slow, or with an irregular rhythm. Tachycardia is generally considered to be a heart rate greater than 100 BPM when the individual is in a resting state and is usually caused when the electrical signals in the upper chambers of the heart function abnormally [4]. A condition known as supraventricular tachycardia (SVT) refers to the condition when the heart rate is closer to 150 BPM or more; this occurs when the heart rate controlling electrical system is out of tune, requiring medical care in conjunction with the patient.

3.1.2. Blood Pressure (BP)

Blood pressure is one of the vital signs that physicians measure to evaluate one's overall health. It reflects the pressure of the blood against the walls of the arteries, given that when the heart contracts, forcing blood into the body, the blood pushes against the inside of the blood vessels. A high blood pressure, a condition known as hypertension, without proper medical monitoring can result in heart problems, stroke, and other medical conditions.

Several factors can increase blood pressure, including stress, smoking, caffeine, excessive alcohol use, certain prescription drugs, low temperatures, and more. Moreover, as people age, they accumulate plaques in the blood vessels, and the flexible walls of the arteries become stiff, resulting in the heart making greater effort to pump blood. Consequently, it starts to fail [5].

Blood pressure is recorded based on the ratio between systolic and diastolic pressure. The first describes the pressure when the heart beats. The second is the period of contraction of the heart before beating again. According to the guidelines announced in November 2017 by the American Heart Association (AHA), measurements of people's blood pressure are organized into the following categories: Normal: Less than 120 mmHg (mmHg) for systolic and 80 mmHg for diastolic; Elevated: between 120–129 mmHg for systolic and less than 80 mmHg for diastolic; Stage 1 Hypertension: between 130–139 mmHg for systolic or 80–89 mmHg for diastolic; Stage 2 Hypertension: at least 140 mmHg for systolic or at least 90 mmHg for diastolic.

Sometimes, people confuse high blood pressure with high heart rate. Blood pressure is the measure of the force of the blood against the walls of the arteries, while heart rate is the number of times the heart beats per minute. There is no direct correlation between the two, and high blood pressure, or hypertension, does not necessarily result in a high pulse rate and vice versa. Heart rate rises during strenuous activity, but vigorous training can only modestly increase blood pressure.

3.1.3. Blood Oxygen Saturation (SpO2)

Oxygen in the blood is one of the important indicators of a healthy body, since it is directly related to body metabolism. Low oxygen saturation in the blood can cause failure in organ functions of the human body, causing serious complications such as necrosis and loss of function.

SpO2 is the measure of the amount of oxygen bound to the hemoglobin in the cells within the circulatory system. This measure provides an estimate of arterial oxygen saturation in the blood. It is presented as a percentage of oxygenated hemoglobin compared to the total amount of hemoglobin in the blood (oxygenated and non-oxygenated hemoglobin). Normal SpO2 values vary between 95 and 100% [5].

Most blood oxygen concentration meters use the finger as a measuring point, as the fingers are thinner and full of capillaries and blood. In [23], IoT-based heart disease monitoring system for generalized health service is proposed. This system monitors the physical signals of patients, such as blood pressure, SpO2, and ECG.

3.1.4. Body Temperature (BT)

The studies presented in [24–26] indicate that the fall or increase of body temperature can be associated with the development of cardiovascular diseases. Sudden death from cardiac causes in athletes should not be mistaken for abrupt death related to heatstroke or malignant hyperthermia. In the second case, the victim has usually exercised excessively in warm weather, often with sporting equipment that disrupts heat dissipation. In addition, during these trainings, people can consume substances that cause increased body temperature and vasoconstriction, hampering the change in body temperature. This situation leads to collapse because with high body temperature irreversible damage in the organ systems can develop [5].

These studies use body temperature monitoring as one of the parameters measured in their research. The investigations [24] and [25] propose remote monitoring of the human body using heart rate (HR) and body temperature (BT) as parameters. The work [26] focuses on the early detection of heart disease where BT is used as one of the predictors for evaluation.

3.1.5. Electrocardiogram (ECG)

In a hypothetical situation, a 31-year-old patient seeks a cardiologist's help in response to pain that afflicts him for 2 days. The patient does not present with any relevant medical history, denies the use of licit and illicit drugs, presents no symptoms of overexertion, and the pain does not improve with rest. The pain began after an argument with his wife. Therefore, the probability of coronary artery disease in this patient is very low [27].

The information provided by a normal electrocardiogram (ECG) has a relatively modest value because it can not greatly reduce the pre-test probability [28]. However, if the ECG reveals changes in repolarization, it is more reasonable to assume that they are due to hyperventilation generated by anxiety than due to myocardial ischemia. Therefore, an ECG altered in this patient also does not modify the pre-test probability of coronary artery disease. Furthermore, alterations of repolarization in the young patient might be a false positive result. The advantages of the ECG are low cost and high availability. However, for the diagnosis of angina pectoris, the Ergometer test (ECG recorded during exertion) is more accurate and the Angio coronarography can confirm suspicions if obstructive lesions are identified in the coronary artery.

The ECG constitutes the record of the electrical activity generated by the cardiac tissue [29]. The traditional ECG uses twelve shunts to record the electrical activity of the heart, involving three bipolar derivations of the limbs (D1, D2, and D3), three amplified unipolar limb shunts (AVL, AVR, and AVF), and six precordial unipolar shunts (V1-V6). The ECG can support a health professional's decision in identifying arrhythmias, ischemia, myocardial infarction, cardiac chamber overloads, inflammatory processes, drug effects, metabolic disturbances, and even diseases causing the risk of sudden death.

The emergence of the IoT as one of the most important interconnected technologies has succeeded in transforming the health care sector. IoT allows ECG devices to be incorporated into customized and interconnected software, but they can also to track their own activity and results along with the activity of other devices connected to them [30]. The studies not only discuss the relevance and applicability of IoT monitoring for ECG, but have also developed systems for ECG monitoring based on IoT. This development comprises a portable wireless acquisition transmitter and a wireless receiver processor [31–33], and [34].

3.1.6. Photoplethysmography (PPG)

Photoplethysmography (PPG) is another method used to measure the heart cycle and obtain heart rate and blood pressure measurements. PPG measures the volumetric change of the heart through the measurement of transmission or reflection of light. As the heart contracts, the blood pressure in the left ventricle, the primary pumping chamber, increases. This increase forces a pressurized “pulse” of blood into the arteries of the body which swell a little before returning back to their previous state. The brightness of a LED light source placed on a spot on the skin increases the pulse pressure, causing a measurable difference in the amount of light reflected back or transmitted which is captured through a sensor.

The amplitude of this signal is directly proportional to the pulse pressure; the higher the peak, the stronger the pulse. Although the signal might be less apparent if measured on the skin at a point more distant to the heart, the change of pressure is sufficient to expand those arteries to a measurable extent. Each peak in the resulting signal can be identified by a special heart rate algorithm that can determine the amount of time between each successive peak, thereby offering another means of measuring heart rate.

Photoplethysmography is an indirect technique; that is, it does not record the true activity that occurs in the heart so it is not always accurate with millisecond measurements. However, the studies described in [35,36], and [37] focus on better accuracy in obtaining the results. If we compare these methods to the ECG, it is possible to demonstrate the ease of measuring the heart rate or blood pressure of an individual. As presented in the survey of [38], this topic that has been studied increasingly in the last twenty years, has shown progress, and seems to demonstrate the clinical applicability of PPG in the diagnosis of CVDs.

3.1.7. Wearable

Constant monitoring might present results in the investigative process of a disease that an ECG might not identify. For instance, an ergometer test or exertion ECG are equivalent denominations of the test that evaluates cardiac work during a physical, scheduled, and progressive effort. It is used in the study of coronaropathy, arterial hypertension, cardiomyopathy, arrhythmias, evaluation of drug efficacy, cardiac rehabilitation, and physical conditioning related to sports.

For heart monitoring over long periods, the dynamic electrocardiography, also known as the Holter system, involves, as a basic principle, the recording of the electrical activity of the heart for 24 hours. To perform the test, the electrodes are placed in the thorax of the patient while wires are connected to an external recording device. Holter is utilized in the diagnostic study of ischemic heart disease, in post-infarction evaluation, pacemakers, sinus node disease, Chagas cardiomyopathy, Wolff-Parkinson-White syndrome, Transient ischemic attacks, and in the disease evaluation of the effect of several drugs.

Portable medical sensors (WMSS) are attracting more and more attention from the scientific and industrial communities. Driven by technological advances in detection, wireless communication, and machine learning, WMS-based systems have begun to transform our daily lives [39]. WMS, initially developed to allow low-cost solutions for continuous health monitoring, now extends far beyond health care. Most of the conventional sensors such as ECG and PPG detect and collect biomedical signals. However, some sensors, i.e., accelerators, collect raw data that can be used to extract health-related information. With continuous performance and improved efficiency in real-time signal processing, the number and variety of WMSs increased significantly from simple pedometers to blood pressure monitors.

The adoption of WMS can offer a long-term health monitoring alternative independent of the patient's location through integration into the more extensive infrastructure of IoT that will provide a better dynamic in the care and diagnosis of patients [40].

3.2. Wireless and mobile heart monitoring systems

The increased popularity of visible technologies opened the door to a IoT-based solutions for health care. Portable health-tracking devices are excellent candidates to minimize the distance between the patient and the doctor.

One of today's most prevalent health problems is the low survival rate of sudden cardiac arrests. All existing systems for predicting cardiac arrest primarily consider heart rate parameters. Some research addresses this problem by concentrating on the analysis and detection of ECG signals that eventually lead to a risk forecast, as abnormal ECG patterns indicate potential heart attack [41].

The use of the smartphone as a resource in the development of an integration platform to monitor and even predict a heart attack is quite beneficial as it naturally combines components of detection, communication, and popular consumption. Currently, this device is widely used to recognize physical activity based on integrated sensors with high accuracy and reliability. For instance, in [31], the focus is to measure ECG in real time with electrodes placed on a smartphone. The collected ECG signal is stored and analyzed in real time through a smartphone application for prognosis and diagnostics. The investigation given in [42] describes an ECG monitoring system composed of a sensor for remote and continuous ECG monitoring for the long term. For monitoring, a smartphone is used that combines the information supplied by the built-in kinematic sensors (accelerometer, gyroscope, and magnetic sensor), to recognize the physical activities of a user and, better yet, the accuracy for the identification of abnormal ECG patterns.

Portable wireless monitoring systems cannot work without an application. This application is responsible for data collection and transmission of messages to those involved in the care process. The use of cloud computing inspired numerous projects in health care services [43]. Within the cloud system, medical data can be collected and transmitted automatically to medical professionals from anywhere and real-time feedback can be provided to the patient. In [44], a method was proposed for ECG monitoring based on the IoT Cypress platform for integrated devices that collects ECG data using a non-intrusive wearable monitoring sensor and in which the data is transmitted directly to the cloud using Wi-Fi.

3.2.1. Body area network (BAN)

Also known as a body sensor network (BSN), BAN is a wireless network of wearable devices that allows the synchronization of different bio-signals to obtain an integrated user profile. BAN operates in close proximity to the human body and can be incorporated into the body through implants or mounted on the surface of the body in a fixed position. The IEEE 802 established a task force called IEEE 802.15.6 for the standardization of the body area network.

IoT-based care distribution models are proposed to monitor human biomedical signals in activities involving physical exertion, incorporating flexibility in calculating the health application, and using device resources available within the user's body area network. For instance, in [45], a case study was conducted monitor the heart frequencies of players during a football match through a smartwatch and the real-time data acquired by this device shows, as foreseen, not only possible situations of sudden death but also injuries.

Wireless sensor technologies assist in the solution of various negative aspects related to wired sensors, which are commonly used in hospitals and emergency rooms to monitor patients,i.e., a conventional electrocardiogram [46]. The various sets of associated threads, cables, and connectors cause discomfort to the patient, restrict their mobility, increase their anxiety, and hinder management for health professionals [47]. Furthermore, the use of wireless connections is less noticeable, reduces patient anxiety, and decreases the possibility of errors in data acquisition. For instance, the system proposed in [48] monitors ECG waves similar to a conventional Holter monitor; it analyzes and supports the decision on the diagnosis of arrhythmia. If arrhythmia is detected, the system sends an alert to the doctor. In [34], an ultrasound prototype was developed as a wearable device and experimental results showed its promising performance compared to that of an electrocardiogram.

3.2.2. Personal Area Network (PAN)

Personal Area Network is a set of ambient sensors surrounding the patient. In health care networks, PANs can be used to connect BANs. The chief use of PAN is to deliver the information monitored by the sensors to external networks or to the next direct node with those sensors. PANs are being widely used in IoT applications such as laptops connected to smartphones.

Bluetooth and ZigBee are some of the technologies used to make PAN available for health care networks. To increase the scope of such local networks, there was a modification of the IPstack to facilitate low-power communication through the IP protocol. One of the solutions is 6LoWPAN, which incorporates IPv6 with low power PANs.

The range of a PAN with 6LoWPAN is similar to the local area networks and the energy consumption is much lower [49]. Studies such as [50] propose, for example, a platform in which 6LoWPAN nodes are attached to biomedical sensors (ECG, blood pressure, accelerometer, body temperature, etc.) to measure and transmit data via PU to RPU for processing and analysis.

3.2.3. Wireless Local Area Network (WLAN)

When one or more PAN networks are connected to a local area network (LAN) wireless, they form a wireless LAN between them. WiFi technology is used by certified products that belong to the class of wireless LAN devices based on the IEEE 802.11 standard. Medical monitoring applications require the account of emergency events as well as the physiological information measured periodically. In critical conditions, the emergency data must have a guaranteed account with an acceptable delay for the specific signal type.

The health system is increasingly enhancing efficiency and results. The adoption and dissemination of IoT can play a significant role in the tenure of health care costs without affecting the quality of the care provided to patients. For instance, as the population ages, the cognitive, physical, and psychological capacities of the elderly vary, affecting the quality of life. Remote monitoring can help in accurate diagnosis and recovery of patients, primarily if it is carried out in the least intrusive way possible and even in the patient's own residence [25].

3.2.4. Cloud

The concept of Cloud is based on the offering of IT resources over the Internet. Presently, one of the greatest challenges facing the field of health care is the need to store, process, and analyze ever-increasing volumes of medical data, images, and studies containing the information of each patient. This crossover of data in the cloud makes it possible to monitor patients outside hospitals, especially when attempting to monitor them in real time.

Patient remote monitoring structures (PPHM) propose to combine IoT, cloud, and WLAN technologies for efficient and high-quality remote health status monitoring. In the case study presented in [51], a patient suffering from congenital heart failure (ICC) who needs regular care at home demonstrates the adequacy of the PPHM infrastructure. In the conventional hospital-centered health system, patients often utilize multiple monitors. The proposed work addresses the challenges of health expenditure, substantially reducing inefficiency and waste as well as allowing patients to stay in their own homes and get the same care or even better.

A major current trend in the health care field is the development of solutions for remote monitoring of the ECG signal using wireless technology. The gateway can be a user-charged mobile device, such as a smartphone, which will serve as a bridge to connect BANs and PANs to a wide-range network (WAN) as shown in [31,52–56], and [57].

We also find other trends such as the studies [58,59] and [39] that present cloud applications or toolkits. These works focus on monitoring heart rate variation (HRV) in real time, integrating portable sensors, cell phones, and a WEB system. Additionally, studies such as the one described in [60] demonstrate the clinical process of hypertension being analyzed through a model based on Business Process Management (BPM). This process is described by a monitoring-based architecture of blood pressure sensors, which in turn includes a mobile application responsible for the analysis of the patient's health monitoring.

3.3. Machine Learning for the heart

Generally, clinical staff use a diagnostic test to anticipate the presence of a disease. A diagnostic test is based on clinical record, physical examination, laboratory sample or other information source. Result analysis must be careful because this can increase or decrease the accuracy of the final medical diagnostic. Techniques of artificial intelligence are been applied in this field [5], one of them is Machine Learning [61].

The Internet of Things (IoT) provides the modernization of the health care sector through the continuous, remote, and non-invasive monitoring of cardiovascular diseases. In [62] an IoT platform for predicting cardiovascular disease using an IoT-enabled ECG system acquires the ECG signal, processes the signal, and alerts the specialist to an emergency. The resources are extracted from the ECG signals and classified by using SVM.

Another example is presented in [63], which proposes that new information related to the physical state of the patient can be remotely captured through a bracelet. The authors proposed the use of linear regression (LM) and Classification and Regression Trees (CART) algorithms to analyze the heartbeat and the detection of heart rate.

Machine learning can be used to create images, identify abnormalities, support areas that require attention, and improve accuracy, efficiency, and reliability of all processes involved in a medical diagnosis. In the study [64], the use of IoT and a neural network-based health risk prediction framework is proposed, presenting an alternative to monitor the health of elderly citizens and prevent the onset of cardiovascular diseases, for example. The results obtained indicate that the proposed structure using IoT has a great added value to ensure that elderly citizens live a healthy life. In [65], authors use artificial neural networks (ANN) for predicting hypertensive in patients and thus, evaluating level of risk of a heart failure. They propose generating continuous alert messages reported by critical changes in blood pressure using only smartphones.

Vital patient parameters such as ECG and temperature are continuously monitored by medical sensors in the hospital. Replacing the traditional methods of parameters being regularly monitored by a nurse with an autonomous system avoids human errors in manually collecting patient data and consequently can reduce fatalities occurring in hospitals and health centers due to human delay and neglect. In [66], an intelligent health care system is proposed, which can regularly monitor patients' conditions and minimize human neglect. The system incorporates Neuro-Fuzzy, which is the combination of Neural Network and Fuzzy logic. The Neural Network adapts and changes to obtain the desired output value for input response changes, which increases the reliability of the monitoring system. Fuzzy logic deals with uncertainty and simulates human reasoning in the diffused data obtained. It logically generates fuzzy rules to make the system robust.

The use of physiological sensors to monitor and assess health becomes ubiquitous in IoT as presented in the studies [67,68], and [69]. An example is provided through the research of [70], which was based on the heartbeat being recorded in wearable devices and sent to a server that links with other patient information and, furthermore, applying SVM and logistic regression to the information; studies have been conducted to predict conditions with and without stress. When people are stressed or nervous, there is an increase in heart rate that can lead to a heart attack. Machine learning has also been used to develop new approaches to counter the IoT limitations, which we will see in more detail in the section Mitigating Key Challenges.

3.3.1. Data fusion for the heart

Additionally, more complex cases have been observed in which a single medical professional does not have enough information, experience, or both to make a diagnosis. Here, the medical advice of health professionals with different specializations should be discussed and correlated with their individual findings to diagnose the issue more accurately. Therefore, the board head can make the final decision, based on the information received. From this perspective, the proposed medical advice resembles a hierarchical organization in which lower-level members provide information for higher-level decision-making [71].

According to Boström, data fusion is the study of efficient methods to automatically or semi-automatically transform information from different sources and different points in time into a representation that provides effective support for human or automated decision-making [72].

Different data fusion strategies have been proposed over the years to reduce the effect of displacement and increase the accuracy of human activity recognition, e.g., in mobile and wearable sensors [73]. According to [74], these approaches can be categorized into Probabilistic methods, which include the analysis of Bayesian sensor values, state space models, maximum likelihood methods, possibilities theory, probative reasoning, more specifically, theory of evidence, KNN, and least squares estimation methods as Kalman filtering. On the other hand, statistical methods include cross-covariance, covariance intersection, and other robust statistics. Moreover, methods of knowledge base theory, which include intelligent aggregation methods, such as RNA, genetic algorithms, and fuzzy logic. Finally, there are methods of evidence reasoning, which include Dempster–Shafer [75], theory of evidence and recursive operators.

Feature fusion strategies provide an excellent means to combine heterogeneous sensor data using machine learning algorithms. Machine learning algorithms such as Vector Support Machine, Artificial Neural Networks [71], Decision Trees and Hidden Markov Model have been used to extract features from different sensor modalities. Besides, to reduce the solving time and to select an optimum feature vector, different methods of feature selection have been proposed. Filter, wrapper, and embedded database approaches are methods for selecting features. These have been critically reviewed. However, the handcrafted features are time-consuming and application-dependent. Recently, deep learning algorithms such as Deep Boltzmann Machine, Autoencoder, Convolutional Neural Networks [76], and Recurrent Neural Networks [77] were proposed for the automatic representation of features to reduce the dependence of manually projected resources and the time spent in the selection of resources.

In [78], the classification of four affective states was performed in different datasets. The authors used k-means as the clustering algorithm to visualize people's emotions. The skin temperature, heart rate, and RMS values were used for grouping the emotional state under happy, sad, neutral, and stressed categories. This work is an example of unsupervised learning that helps to find the intrinsic constitution of the data. In [79], the proposed wearable IoT system introduces the use of a new data fusion sensor for data management. For this, the authors apply a Bayesian approach, making it possible to detect and classify different types of physiological states of people.

3.4. Mitigating key challenges

In this subsection, we present a brief description of some technologies applied to medical processes.

3.4.1. Energy and signals

The technology applied in health care has revolutionized the processes of diagnosis and treatment of diseases, reducing the chances of errors and allowing greater accuracy in choosing the most appropriate treatment for a specific pathology. However, similar to how a new drug is evaluated until it obtains approval and gets released in the market, a new device or system associated with health must be examined through careful studies and simulations so that it can be reeased as a new resource for the benefit of decision makers and especially the patients. For instance, for accessible monitoring of cardiac health via photoplethysmography (PPG), it is necessary to guarantee an accurate detection of the cardiac condition from the signals extracted from a smartband or any other similar device that intends to capture the parameters.

The presence of noise primarily due to motion strongly affects the result of the PPG analysis. The study [80] states in its proposed method that physiological signal involves preprocessing, specifically the breakup, and can substantially improve the overall performance efficacy and clinical utility as demonstrated in the case study, which shows a significant improvement in efficiency when identifying coronary artery disease (CAD) from the PPG signal.

Heart rate monitoring using pulsed PPG signals during intensive exercise is a subject studied in [35,36], and [26]. As the signals get corrupted due to extreme movement disorders caused by abrupt hand movements, Zhilin Zhang, Senior Member of IEEE, in his studies [35] and [36] proposes and compares with techniques used, a general framework called TROIKA, comprising a signal decomposition for the dismemberment, signal reconstruction spectrum, spectral analysis, and verified spectral data analysis. Already in [26], a new technique was presented to accurately determine the heart rate during excessive movement by classifying PPG signals obtained from smartphones or wearable devices combined with motion data obtained from accelerometer sensors. The approach uses the IoT cloud connection from smartphones to PPG signal selection using deep learning.

Recently, wearable devices were used for long-term monitoring of ECG signals. However, the comfort of monitored patients was not satisfactory, and therefore a well-designed textile electrode with excellent signal quality and comfort (SQC) is essential for acquiring ECG signals. In [81], in order to provide optimization of the SQC, a textile electrode with mesh structure and conductive material comprising silver coated with cotton and nylon fiber is studied. This textile compound is integrated into a blouse with a miniaturized wireless detection platform to collect ECG signals from the volunteer.In [82], the authors focused on the evaluation of the signal quality in real time (SQA) and the slight detection of QRS for the application of a visible ECG. For that, the study proposes a method of combining several SQIs and learning SVM-based machine to automatically classify the signal quality of ECGs acquired in rest, outpatient, or physical activity environments.

Previously selected researches describe monitoring the vital signs of patients to predict its health status by using applications of the Internet of Health Things. In order to reach this objective, electronic health systems are principally based on sensors in the environment. The work [83] proposes a method to predict both the ECG sensor data and the most likely health condition of the patient, which does not need a common method of activity recognition to predict the patient's health situation. The proposed approach provides for future mobile sensor data and overall patient health status using a semi-Markov (HSMM) model with two outputs.

A common issue with wearable technology is that signal capture and transmission requires power, and as such, devices often require frequent recharging, which is a limitation to the continuous monitoring of vital signs. To mitigate this, [84], and [85] advocated the use of lossy signal compression to decrease the data size of the collected biosignals and consequently increase the battery life of wearable devices. [86] presents a new wearable wrist ECG, proposing heart monitoring with low energy consumption and customizable electrodes through the use of silver paint applied on the housing of the device. The design employs a few active components to minimize energy. The ECG front end is integrated with an existing IoT backend for use on the wrist, and the device's performance has been compared to other commercial devices, showing its accuracy to a few beats per minute. Assuming moderate periods of user-activated sampling, the system can last for more than a month using the supplied battery and weighs less than 30 g including the battery and the wrist strap.

3.4.2. Security and privacy

The factor of BSNs collecting sensitive data and generating valuable information for caregivers and users makes them attractive targets for technology criminals. One such threat is sensor compromise, such as unauthorized modification of the sensor output (i.e., measurement) to relay incorrect patient health data to the base station. For instance, tampering with the ECG sensor can have severe consequences for the user as it monitors the cardiac process. One study [87] examined attacks associated with handheld devices. proposing ways to delegate usage to a wide variety of restricted handheld devices to ensure the privacy and integrity of their data.

Traditional encryption techniques are disadvantageous when preventing data analysis in a cloud environment (unless the decryption keys have been sent to the cloud provider). In [39], this disadvantage is overcome by implementing Homomorphic Encryption (HE). In this study, the researchers proposed a new system that analyzes ECG data, aggregates data on the PC, uploads to the cloud service provider (such as Amazon Web Services), examines data in the cloud environment (and forwards the data/results to the doctor in question), and also protects the entire route with the help of the HE technique. Subsequently, the cardiologist requests to observe the patient's HRV result for a specified interval and the results are extracted from the cloud server, decrypted, and displayed. Finally, the cardiologist reviews the results, diagnoses the patient, and decides on an appropriate treatment strategy. Pulse-based random binary sequences (RBSs) are the backbone of various safety aspects of wireless body sensor networks (WBSNs). To improve the efficiency of time, a technique of generating biometric RBSs using interpulse intervals (IPIs) of the heart rate is developed in [88]. According to the experimental results, 128-bit generated RBSs from healthy individuals and patients can potentially be used as keys to encryption or entity identifiers to protect the WBSNs. However, the study of Liang et al. [89] incorporates the safe and convenient sharing of personal health data, confronted with privacy issues and existing vulnerabilities in the storage of current personal health data and systems, as well as the concept of ownership of self-patient-based health data sharing solutions supported by blockchain technology. In [90], the proposed processor reuses the ECG features used during classification to generate a key to protect the proposed IoT platform against hardware- and telemetry-based attacks.

The use of techniques to conceal the existence of a message within another such as steganography, demonstrated by [91] to hide patient diagnostic information on the ECG signal, based on the intelligent compensation coefficient, proved to be a safe alternative. To provide a high concealment capability, the proposed method incorporates two bits of data into a coefficient packet from the host ECG signal at a time. The simulations presented indicate a superior ability to hide, and besides, the method is tolerant of attacks such as inversion, translation, and additional attacks by Gaussian noise, which is rare in conventional steganographic ECG schemes.

3.5. Opportunities from the IoT for heart

Portable devices and smartphones are a trend all over the world. Among their uses are storage of images, sounds or personal documents. In addition to the device's internal storage, user data can be stored in services in the cloud, thus facilitating access to all locations. [92] explores the use of ECG records to encrypt user data and addresses this challenge by proposing EbH, a mechanism for generating symmetric keys based on ECG.

In recent years, the adoption of biometric methods for authentication and access control has been increasing, for example, the adoption of biometric reading captured by the palm to access banking data. In [93], a computational method is presented identifying a person using only three features based on ECG Morphology from a single heartbeat, which aims for scenarios of low computational cost.

The adoption of IoT in heart care brings a range of new opportunities in the manner it addresses the diagnosis and treatment of heart disease. If previously the doctor had to wait for the patient's visit to perform the initial anamnesis, today, through a real-time monitoring network, one can obtain the patient's current status as well as predict extreme situations, for instance, a heart attack that can in many cases lead to death or leave sequelae that are costly both to the health care structure and especially to the patient.

Researches such as [24,94–96], and [55] focus on developing systems for detecting a heart attack with IoT support and [41] proposes an early prediction system for cardiac arrest using the same vein of research, that is, collecting from sensors such as a pulse sensor (*); using an IoT device such as an Arduino Uno or even a smartphone to transmit the data collected by the sensors outside the BAN topology, (the patient themself), and indirect systems correlated with emergency care professionals so that they can act on the detected health incident in the fastest possible way.

Presently, a vehicle contains numerous sensors that help to monitor its operation and if an abnormality is identified, the driver is informed that it requires technical assistance for a thorough check conducted by a specialized professional team. This situation suggests that the monitoring is done correctly and obeys the standards stipulated in studies and through detailed analysis has ensured substantial reliability in the use of this means of transport. In the human body, this is no different. If one practices healthy habits, performs constant monitoring, and is assisted by skilled professionals, the likelihood of further health problems in the future decreases. This does not mean that issues will never occur, similar to how even with monitoring, a vehicle can undergo an incident with a pothole, causing its disrepair. Therefore, a health problem can occur during the journey of life even with all the monitoring technology and treatments we have today; our aim is to reduce the probability through stochastic processes.

Studies such as [42,48,88,97–102], and [103] elucidate the benefits of using IoT to mitigate diseases associated with an abnormal heart rate. In iCarMa [97], an on-demand cardiac monitoring scheme distinguishes cardiac conditions using only the PPG signal extracted from a smartphone camera or other sensors and also classifies abnormal cardiac conditions such as asystole, extreme bradycardia, extreme tachycardia, ventricular flutter, and ventricular tachycardia to indicate severity. The use of the ECG signal captured by wearables devices to develop learning, classification, and prediction models for the automatic detection of cardiac arrhythmias is the pillar of the studies [98–101], and [88]. The IOT-BEAT, which calls itself an intelligent nurse for the cardiac patient, [48] proposes a system that monitors ECG waves similar to the existing Holter monitor and also attempts to predict the occurrence of arrhythmia. In the case where the waves are of normal significance, the heart is functioning properly; our system would send a regular report to the doctor at regular intervals. Furthermore, in [103], a light-based sensor is used to check heart rate variations because the study focuses on atrial fibrillation, which is a major cause of stroke, heart failure, and other heart-related complications. Hence, a reliable method of detection is required to intervene before the condition worsens. One of the chief goals of this research project is to build a low-cost PPG sensor, and this is achieved by using a combination of LED photodiodes to emit light and examine the reflected light.

In addition to heart rate, monitoring of blood pressure has become the focus in several studies related to the use of IoT for health as demonstrated in [60,104,105], and [106]. Chronic diseases such as hypertension and hypotension, in the long run, can lead to serious illnesses. They are already identified and subsequently accompanied by carriers of the same through readings of diastolic blood pressure (the minimum pressure) and systolic blood pressure (the maximum pressure) generated by sensors that can be interconnected in a PAN network and later integrated into a medical monitoring structure.

The use of sensors and electronic circuits are required to derive the readings obtained from the ECG in conjunction with PPG signals to capture blood pressure from a smartphone as demonstrated in the prototype developed by [104]. This study illustrates that a low-cost device can be easily extended to monitor cardiac characteristics such as premature ventricular contraction and venous pulsations. The studies of [60,105], and [106] demonstrate that monitoring blood pressure through IoT brings social and economic benefits such as improvement in the health process that requires interdisciplinary cooperation and coordination among medical teams, clinical processes, and hypertensive patients.

The optimal opportunity to improve quality of life (QoL) standards has been demonstrated in [105] and [107]. These studies have added medical value to a smartwatch such as making it predicting a drop in blood pressure (BP) which might cause dizziness and increase the risk of falling in the elderly as well as in younger groups [105] by providing suggestions regarding habits consistent with their current physical state. These include diets or sports through non-invasive monitoring of blood pressure [107].

According to the European Union, Smart Cities are systems of people interacting and using energy, materials, services, and funding to catalyze economic development and improve the quality of life. These interaction flows are considered intelligent for strategically using infrastructure and services and information and communication along with urban planning and management to meet the social and economic demands of society. The electronic health applications in IoT networks, especially for intelligent management of medical resources in the city, have been attracting many researchers.

In [94], the authors propose a new IoT electronic health service for detecting real-time heart attacks (RHAMDS) through voice control and gesture control using smart clocks in conjunction with Software Defined Network (SDN). SDN a network paradigm innovative approach that allows network programming by separating the data plan and control plane, thereby providing global intelligence for the network. RHAMDS aims to improve emergency response time for heart attack patients in particular vehicle networks and to prevent possible collisions of vehicles generated by this incident. [108] focuses on developing a reliable and low-cost health monitoring system for automotive drivers. It is based on the principle of contactless ECG and sending data to the cloud. Multiple-signal acquisition ECG electrodes are placed in the seat and seatbelt of the automobile and the received signals are sent to a web server which can be analyzed by expert decision-makers to provide an immediate response in case of emergency.

Remote monitoring is extremely useful for hospitals facing insufficient infrastructure to admit new patients. Studies such as [48] and [56] aim to disseminate cardiac care to urban and rural locations using the advantages of IoT in health to remotely monitor the ECG signals of the afflicted cardiac patients, alerting those responsible for health in case of an emergency, thus solving the problem of stocking hospital structures as the patient could be monitored from his or her residence. The work [109] presents a smart stethoscope that can visualize sound signals from the heart and simultaneously measure the electrocardiogram (ECG). This device has proved to be suitable for elderly people and for people who suffer from chronic diseases.

3.6. Lowering the cost in IoHT

The prototypes presented in the articles reviewed in this survey chose to use low-cost hardware to perform their experiments such as in [110] and [111]. This does not imply that the same can not be used in a production environment; [31,33,112], and [52] propose the use of their infrastructure presented for future adoption as products available for an assisted living environment. For these solutions to be competitive, improving them for usability in such a complex health environment must be accomplished as they need to provide high levels of robustness for all the involved resources provided, from communication with sensors for automatic monitoring to visualization and storage of sensor data [113].

For instance, the objective of the work of [110] is to create a daily monitoring module which will allow obtaining a high-precision ECG, processing it, and transmitting it through the Bluetooth Low Energy (BLE) wireless interface. Modern electronic components (ADAS 1000-4 BSTZ, CC2650MCU) are used in this device. The patient's signal through the electrodes is supplied to the ADAS 1000-4 BSTZ ECG chip which produces scanning, filtering,and signal amplification. Additionally, the data is sent to the microcontroller via the SPI wire interface. Here, the data is processed and transmitted through the part of the network via the BLE to the switch. The CC2650 was chosen as the MCU. The real-time operating system created by Texas Instruments (TI RTOS) was used as a basis for writing software for the CC2650 microcontroller (MC). Furthermore, Code Composer Studio 7 (CCS 7) was chosen as a development environment. In [111], the researchers attempted to adapt various short-range technologies for WBANs in ubiquitous health monitoring. For this, we used a BLE wireless module called BLE112 from Bluegiga which is based on the CC2540 model from Texas Instruments. BLE112 can host complete end-user applications without using an external host or microcontroller and provides host interfaces such as UART in applications where the external host is required.

In [112], the author proposes a tutorial on designing a smart bracelet to monitor heart rate. The monitoring hardware comprises BLE Nano, Pulse Sensor, and a battery mounted in a box created in a 3D printer. He used a low-cost sensor easily found in the market and as presented in Table 002, many of these were identified to have been used in prototypes presented in the studies selected for our evaluation. In [33], the Arduino-based microcontroller was used as a gateway to communicate with various sensors such as the temperature sensor, ECG sensor, pulse oximeter sensor, etc. The microcontroller collects the sensor data and sends it to the network via Bluetooth using the Bluetooth interface module for Arduino. This article essentially explains the detection of abnormalities in the heart through a specially designed ECG circuit and the transmission of the relevant data to a smartphone via Bluetooth.

Unlike most existing methods that use an optical sensor to monitor heart rate, in [31] the approach is to measure real-time ECG with dry electrodes placed in the smartphone case. The proposed hardware comprises a single chip microcontroller (RFduino) built-in with low power Bluetooth (BLE) which thus decreases the size and extends the battery life. A smartphone box was created using a 3D printer to validate and analyze the system's viability. In [52] the development of a project for ECG monitoring was presented that also used a smartphone, but this time, it was used as a hub between the sensors used to pick up and treat the ECG signals to send them to a cloud server.

The studies [98] and [60] use low-cost solutions in IoT to develop the proposals of their research. [98] describes the methods used to train the ECG classifiers and their predictive aspect because once abnormal beats or waveforms are detected, the appropriate alarms can be issued and sent to the health care agency in charge of patient care. For a case study, a real-time intelligent IoT (Internet of Things) system that can be integrated with the GP Connect infrastructure provided by the NHS, UK, was proposed. A data analysis software was developed with GCC WFDB, the libraries were provided by the MITDB BIH, and arrhythmia was hosted on a Linux IoT device that could be a Raspberry Pi or Beaglebone Black.

In [60], a model of empowerment of hypertensive patients through BPM, IoT, and remote sensing was proposed for which a web system connected with health monitors, environment sensors, and a mobile application was utilized. To capture the environmental information, a prototype of a system for temperature and atmospheric pressure monitoring was developed; these are two variables that affect hypertensive patients. A Raspberry PI v3 unit was used as a hardware platform because it is robust and has low power consumption, which makes it suitable to support a service that works continuously, allows the connection of sensors such as the BPM180 that is used in the experiment, and has wired and wireless communication interfaces required to transmit monitored information.

In addition to the acquisition of low-cost hardware, many open source solutions for the development of web applications, or Apps created for the architectures, proposed in the selected studies were used; see [56,60,114]. In [60], to support the life cycle of the proposed BPM model, the Bonita Community Edition version 7.4 software was used. Bonita is a modular, open source BPMS that implements BPM's complete life cycle. With this tool and in collaboration with a medical team, all procedures associated with the clinical process of the proposed redesign were designed. For web development, AngularJS was used which is an open-source JavaScript framework maintained by Google [60].

In [114], the prototype includes an alarm system that sends a message to the phone application and, when using social networks such as Twitter, timely notifies the attending physician and the patient's relatives whenever a critical level in the patient's body signals is detected. To create an Android OS app to view flow data and manage alert messages at critical levels, MIT App Inventor 2 was used. App Inventor is based on a block diagram programming that allows one to manage different aspects of the mobile device such as notifications, web access, calls, and messages. Emergency notification management is possible due to the Twitter Developer App linked to the created app. Thus, when an emergency warning is posted to a Twitter wall, an audio message and the display of emergency options also appear. App Engine, a platform for creating Web applications and mobile backends with automatic escalation, was used in the telemedical health system, developed by [56] and based on a mobile communication platform called ECG for Everybody, for the implementation of the web platform.

To address the needs generated by increasing the variety and quantity of data generated by IoT-based health monitoring devices, researchers have begun to use large data and NoSQL (Unstructured Query Language) technologies. The IoT framework proposed by [56] for early detection of heart disease uses the open source database NoSQL Apache HBase to store the huge data volume of the sensors. These were used in the cloud which was also used to propose a system that will detect heart attacks with the help of different aspects, for example, monitoring heart rate and smart blood pressure [95].

IoT is a scenario in which most devices are resource constrained, which means that intelligence will be delegated to a more capable entity. This entity is a software identified as IoT middleware or IoT middleware platform [54]. For instance, studies such as [44] and [115] used the Amazon Web Services (AWS) IoT Cloud and in [115] the Microsoft Azure IoT Suite.

4. Discussion and reference model

This section presents a discussion and comparative analysis of the proposals presented by the authors of the research reviewed in this survey. Moreover, those that were tested by volunteers or simulated only from data captured in research bases were also scored. Table 1 summarizes all the points covered in Section 3 and scored in the selected articles. This table includes signs, communication whether machine learning algorithms were used, whether cardiovascular diseases were addressed, how they collected signals for validation of the presented proposal, and whether the computational resources used in the experiment were described.

As the proposal of this survey is also intended to be a support material, we present a reference model based on the evaluation of the resources used by the authors of the studies selected in this research. This model aims to help future enthusiasts discover and subsequently enumerate the factors necessary for the development of a prototype for online heart monitoring purposes, including facilitating the identification of the resources required for future study.

4.1. Discussion

Next, we will discuss points for the development of a prototype to present the concept, model, or solution to a problem that was delimited in the research selected in this survey. Tables 2–4, as shown in Fig. 2, summarize the technological resources of the studies that respectively emphasized prototyping, application development, and homologation environment.

The following conclusions can be drawn regarding the resources used by the authors:

- The authors emphasized using low-cost computing resources such as the Pulse Sensor for signal collection. For projects involving sets of hardware logic and not requiring the use of robust software behind, the Arduino platform was the most chosen. Raspberry Pi cards, which can also work in applications involving hardware logic, have been explored in cases requiring optimized software solutions such as in machine learning algorithms; after all, these are complete computers. The IoT platform Intel Galileo was used promptly in the study of [101].
- We have found that the integration of wearable sensors into mHealth applications is still being explored by researchers for the regular use of activity trackers and biosignals in their experiments. The use of the smartphone associated with a smartband such as the MI BAND 2 that jointly forms a Personal Sensor Device (PSD) was used in some studies that aimed to demonstrate the integration of personal health devices converged with attendant networks, as illutrsated in [120].
- As emphasized in this paper, the use of low-cost resources by the authors was evident, because one of the aspects that are frequently emphasized in the adoption of IoT in health is the possibility of reducing costs. We correlate this to the approval of Android as an operating system used in the proposals presented by the authors using mobile applications as part of their research, such as [31,52,58,96,114,122], and [37], and even those using platforms such as MIT APP Inventor 2 for development. However, for a more comprehensive adoption of a project related to the use of a mobile application, the development of an iOS version should be considered.

Table 1
General selection.

Proposed approach	Signal type				Signal capture		Communication method				Machine learning	Mitigated challenges		Heart diseases	Samples Data	
	HR	BP	SPO2	BT	ECG	PPG	BAN	PAN	WLAN	CLOUD	DESC	SIG	SEC	DESC	MED	VOL
Samr and Mohammed 2017 [94]	x								x	x		x				
Ometov et al. 2017 [87]	x								x	x			x			
Natarajan and Vyas 2016 [84]	x				x	x	x		x			x				x
Mahmud et al. 2016 [31]	x				x		x		x	x		x	x	x		
Hooshmand et al. 2016 [85]	x	x	x		x	x			x		x	x				
Jindal 2016 [26]	x					x				x	x	x				x
Mosenia et al. 2017 [15]	x	x	x	x	x		x	x	x	x	x	x	x	x		
Tomasic et al. 2016 [67]					x				x		x	x				
Walinjkar and Woods 2017 [98]	x	x			x					x	x	x	x	x	x	
Khairuddin et al. 2017 [30]	x				x		x		x			x		x		
Chen and Chuang 2017 [116]	x				x		x	x	x	x		x		x		
Zhang 2015 [35]	x					x						x			x	
Zhang et al. 2015 [36]	x					x						x			x	
Xin and Wu 2017 [107]		x				x	x	x	x	x		x		x		x
Ukil et al. 2016 [80]	x	x				x					x	x		x	x	x
Gowrishankar et al. 2017 [24]	x			x		x	x	x	x	x		x		x		
Mora et al. 2017 [45]	x	x	x	x	x		x	x	x	x	x	x	x	x		x
Priya et al. 2016 [25]	x			x			x	x	x	x		x				
Manisha et al. 2016 [95]	x	x				x	x	x	x	x				x		
Tseng et al. 2015 [117]		x	x		x		x	x	x		x	x		x	x	x
Singh et al. 2016 [108]	x				x		x	x	x	x		x				x
Nurdin et al. 2017 [118]	x				x		x	x	x	x		x		x		x
Kumar and Gandhi 2017 [119]	x	x	x	x			x	x	x	x	x	x		x		
Kang and Larkin 2017 [120]	x	x		x			x	x	x	x	x	x				x
Sidheeque et al. 2017 [96]	x	x		x		x	x	x	x	x				x		
Baig et al. 2017 [16]	x	x	x	x	x	x	x	x	x	x	x	x	x	x		
Gusev et al. 2017 [55]	x			x	x		x	x	x	x		x		x	x	
Vysiya and Kumar 2017 [99]	x				x		x			x	x	x		x	x	
Hussein et al. 2017 [115]					x		x	x	x	x	x	x	x		x	
Puri et al. 2016 [97]	x				x	x	x	x	x	x	x	x		x	x	
Keshan et al. 2015 [68]	x				x						x	x		x	x	x
Yasin et al. 2017 [90]	x				x		x	x	x	x	x	x	x	x	x	
Constant et al. 2015 [112]	x					x	x	x				x				
Thai et al. 2017 [32]	x				x		x	x			x	x		x	x	
Rao et al. 2017 [121]	x				x		x	x	x		x	x		x		
Penmatsa and Reddy 2016 [33]	x		x	x	x		x	x	x	x		x				x
Constant et al. 2015 [122]	x					x	x	x	x	x		x				x
Mohana and H. V. 2015 [123]	x						x	x	x			x				
Zhou et al. 2017 [58]	x				x		x	x	x	x		x				
Choudhury et al. 2015 [37]	x					x	x	x				x				
Shahshahani et al. 2017 [34]	x						x	x				x				
Paiva et al. 2017 [93]	x				x		x	x			x	x			x	
Satija et al. 2017 [57]	x				x		x	x	x	x	x	x		x	x	
Dinh et al. 2018 [104]	x	x			x	x	x	x	x	x	x	x				x
Yang and Wang 2018 [91]					x	x	x	x	x	x	x	x	x		x	
Li et al. 2017 [23]	x	x	x	x	x		x	x	x	x		x		x		x
Kirtana and Lokeswari 2017 [106]	x	x		x	x	x	x	x	x	x		x	x	x		x
Iakovakis and Hadjileontiadis 2016 [124]	x	x			x	x	x	x			x	x		x		x
Cai and Venkatasubramanian 2015 [69]	x				x		x	x			x	x		x	x	
Montalvo et al. 2016 [114]	x		x	x		x	x	x	x	x		x		x		
Piwek et al. 2016 [125]	x	x	x	x	x	x	x	x	x	x			x	x		
ElSaadany et al. 2017 [41]	x			x	x		x	x	x		x	x		x		x
Shah and Danve 2017 [100]	x				x		x	x	x	x	x	x		x	x	
Azariadi et al. 2016 [101]	x				x		x	x	x		x	x		x	x	
Nigam et al. 2016 [48]	x				x		x	x	x	x	x	x		x	x	
Yoo and Chung 2017 [126]	x			x	x		x	x	x	x		x	x	x		
Chen et al. 2015 [127]	x					x	x	x	x		x	x				
Rizqyawan et al. 2017 [52]					x		x	x	x	x		x				x
González-Manzano et al. 2017 [92]					x		x	x	x		x	x	x		x	
Teixeira et al. 2017 [128]	x				x		x	x	x			x				
Jokic et al. 2016 [56]	x				x	x	x	x	x	x		x		x		
Spanó et al. 2016 [129]	x				x		x	x	x	x	x	x				
Makarova et al. 2016 [105]		x					x	x	x			x		x		
Hasani and Jafari 2017 [130]	x						x	x	x	x	x	x			x	
Noh et al. 2017 [131]	x				x		x	x	x	x		x			x	
Vlasov et al. 2017 [110]	x				x		x	x	x	x	x	x		x	x	
Yang et al. 2016 [53]	x				x		x	x	x	x	x	x		x	x	
Ruiz-Fernández et al. 2017 [60]		x		x		x	x	x	x	x		x		x		x
Touati et al. 2015 [111]	x				x		x	x	x			x				
Gia et al. 2015 [132]	x	x	x	x	x		x	x	x	x	x	x		x	x	
Krachunov et al. 2017 [86]	x				x		x	x				x				

(*continued on next page*)

Table 1 (*continued*)

Proposed approach	Signal type				Signal capture		Communication method				Machine learning	Mitigated challenges		Heart diseases	Samples Data	
	HR	BP	SPO2	BT	ECG	PPG	BAN	PAN	WLAN	CLOUD	DESC	SIG	SEC	DESC	MED	VOL
Düking et al. 2016 [133]	x		x	x	x	x	x	x	x			x				
Hsu et al. 2016 [134]	x		x				x	x	x	x	x	x		x	x	
Casilari et al. 2016 [135]	x			x	x		x	x			x	x				x
Vemishetty et al. 2016 [136]	x				x		x	x	x	x	x	x		x	x	
Yamamoto et al. 2017 [137]	x			x	x		x	x				x				
Antony et al. 2016 [17]	x			x	x		x	x	x	x	x	x	x			
Cho and Park 2016 [138]	x															
Sharmila and Veronica 2017 [139]	x				x		x	x	x	x		x				x
Hussein et al. 2018 [39]	x				x		x	x	x	x		x	x	x	x	
Deshpande and Kulkarni 2017 [44]	x				x		x	x	x	x	x	x	x	x		
Miao et al. 2015 [42]	x				x		x	x	x	x		x		x		x
Mumtaj and Umamakeswari 2017 [66]	x				x		x	x	x	x		x		x		x
Sethi and Sarangi 2017 [49]	x	x	x	x	x	x	x	x	x	x	x	x	x			
F. Touati et al. 2015 [50]	x	x	x	x	x		x	x	x	x		x				
Abawajy and Hassan 2017 [51]	x				x		x	x	x	x	x	x	x	x	x	
Cruz et al. 2018 [54]									x	x			x			
Chen et al. 2017 [18]	x				x		x	x	x	x	x	x		x		x
Pandey 2017 [70]	x			x		x	x	x	x		x	x		x		x
Gnecchi et al. 2016 [88]	x			x	x		x	x	x	x	x	x		x	x	
Farahani et al. 2017 [14]	x	x		x	x	x	x	x	x	x	x	x	x			
Wu et al. 2018 [81]	x				x		x	x	x			x				x
Prajapati and Bhargavi 2018 [64]	x	x	x	x			x	x	x	x	x	x		x		
Menychtas et al. 2018 [113]	x	x			x		x	x	x	x		x	x	x		
Bathilde et al. 2018 [103]	x					x	x	x				x		x		x
Pirbhulal 2018 [140]	x				x		x	x	x			x	x		x	x
Haripriya 2016 [141]	x	x	x	x	x		x	x	x	x		x				
Liang 2017 [89]	x						x	x		x			x			
Tien 2017 [142]	x							x	x	x	x	x	x	x		
Moraes et al. 2018 [38]	x	x	x	x	x	x	x	x	x	x		x		x		
Nweke et al. 2019 [73]	x	x	x	x	x					x	x	x	x			
Dautov et al. 2019 [71]	x			x						x	x	x		x		
Pires et al. 2016 [74]	x									x	x	x				
Esposito et al. 2018 [75]	x									x	x	x				
Chandra et al. 2019 [76]	x	x			x		x				x	x			x	
Bin and Jiangyong et al. 2017 [77]	x			x	x		x	x			x	x				
Orpwood et al. 2015[78]	x			x			x				x	x				
Sanfilippo and Pettersen et al. 2015 [79]	x				x		x	x	x	x	x	x		x		
Liu et al. [82]	x				x		x	x	x	x	x	x		x		x
Tariq et al. [63]	x				x		x	x	x	x	x	x			x	
Sood and Mahajan [65]	x	x					x	x	x	x	x			x		
Sasidharan et al. [102]	x	x	x	x		x	x	x	x	x	x			x		
Lin et al. [109]	x				x		x	x	x	x	x			x		x
Zamanifar and Nazemi [83]	x				x		x	x	x	x	x			x		x
Devi and Kalaivani [62]	x				x		x	x	x		x			x		

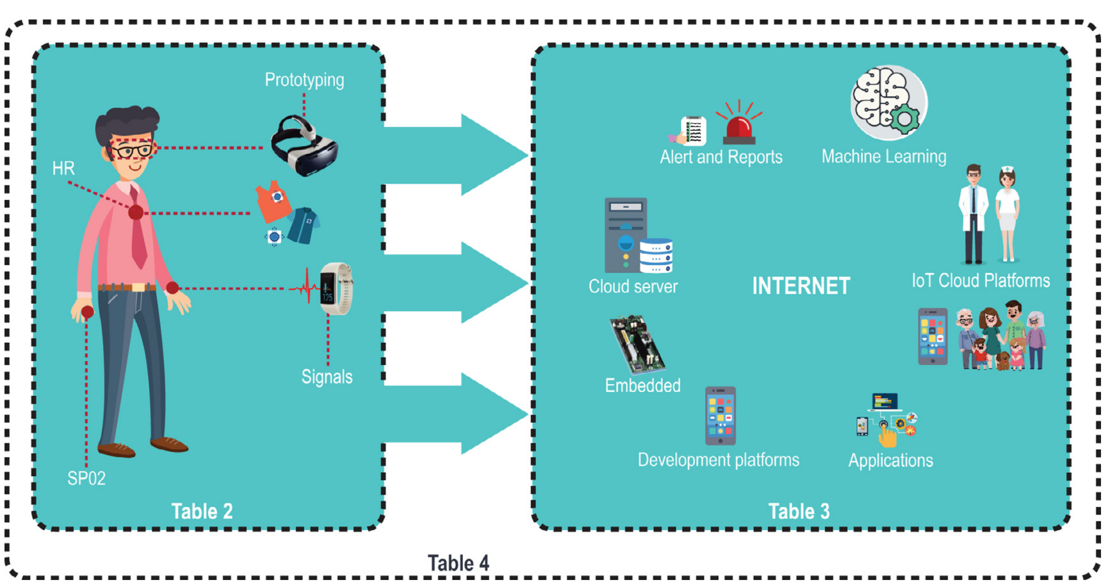

Fig. 2. Development framework.

Table 2
Prototyping.

Proposed Approach	Application Description	Hardware and Software Description
Mahmud et al. 2016 [31]	Design and prototype focused on measuring and monitoring electrocardiogram (EKG) in real time using Smartphone. The approach is to measure EKG in real time with dry electrodes placed in the smartphone case. The collected EKG signal can be stored and analyzed in real time through a smartphone application for prognosis and diagnosis.	The proposed hardware system consists of a single chip microcontroller (RFduino) embedded with low power Bluetooth (BLE), thus miniaturizing the size and extending the battery life. For this project, an Android application was developed to obtain and display real-time data from physical electrical circuits.
Walinjkar and Woods 2017 [98]	The research initially focused on constantly monitoring wearable EKG 3-lead EKG readings so that later on the IoT EKG device performed the real-time analysis to identify and predict cardiac risk as an arrhythmia consequently.	Oliméx 3-lead EKG device connected to an Arduino microcontroller that transmitted samples to a Linux IoT device (Raspberry Pi or Beaglebone Black) with data analysis software trained using MITDB Arrhythmia DB and MATLAB WFDB.
Gowrishankar et al. 2017 [24]	A proposed parameter of remote sensing of the human body consisting of pulse and temperature. The parameters used for detection and monitoring will send the data through wireless sensors. Detection data will be collected and used to inform the patient of possible diagnoses.	LM35 sensor was used to measure the BT of the human body and press the sensor for the HR. After, the ESP8266 module was connected to the Arduino UNO for communication via WIFI.
Priya et al. 2016 [25]	The authors propose a Low Cost BT and HR Monitoring System using RFID technology.	The proposed hardware consists of a PIC microcontroller in conjunction with the temperature sensors MCP9800 and heart beat sensor AD8232 and the RFID Reader for communication. The software used was the MPLAB IDE.
Sidheeque et al. 2017 [96]	A heart rate monitor and a heart attack detection system is proposed by using the Internet of Things.	The prototype used the pulse sensor to capture the HR signals in conjunction with an Arduino UNO for communication. The results are demonstrated in the Android application designed by the authors.
Puri et al. 2016 [97]	A low-cost self-triggered arrhythmia cardiac management solution is presented. In deep, this device is accurately detecting and removing movement artifacts on PPG signals ensuring accuracy in detecting the arrhythmia condition, specifically to reduce false negative alarms and thereby address the need for health monitoring for early detection of cardiac conditions such as bradycardia, tachycardia, ventricular flutter, and ventricular tachycardia.	It acts as a local analytic engine on the host machine. The built-in host camera (such as a smartphone or a smartwatch) is required to capture the video sequences from the bloodstream in order to extract the PPG signal.
Constant et al. 2015 [112]	The authors explain how to develop a smart bracelet to acquire PPG signals and estimate the heart rate (HR) in real time.	BLE Nano was programmed using the MBED compiler along with the MK20 USB board. The housing consists of two separated parts: the first one presents a rigid housing that provides a structure that housing all components. The second one consists of a flexible adjustable range that allows the device to be used by a user and it is manufactured using 3D Fusion printing.
Constant et al. 2015 [122]	A Pulse-Glasses was designed. This device is a smart glasses connected to the cloud, for discrete and continuous HR monitoring.	The frame was generated on a 3D printer, and the pulse sensor next to the nasal canals was subsequently installed for HR data collection. The Arduino Blend-Micro was also built into the frame to serve as a gateway for communication via BLE. This technology was installed as an Android application, and it is responsible for the analysis and presentation of the monitored data.
Yamamoto et al. 2017 [137]	This study proposes a new structure and fabrication by using the “kirigami” concept to realize a flexible multifunctional flat-type integrated patch with an acceleration sensor for motion detection, a skin temperature sensor, and an EKG sensor.	The manufacturing process of the planar multifunctional flexible printed patch was: Ag electrodes were printed on the upper and lower surfaces of a PET film as electrodes and EKG sensor, respectively. The PET film was then cut using a laser cutter for kirigami structure and acceleration sensor beams. Deformation sensors formed by the mixture of carbon nanotubes (CNT) and Ag nanoparticles (AgNPs) were formed in the acceleration sensor beam.
Pandey 2017 [70]	DDevelopment of an IoT device to measure the level of stress via the heart rate as one of the parameters and along with ML alarm the situation when the person is at real risk.	Prototype includes the Pulse Sensor and Arduino UNO. The proposed application is developed in Python and stored on a Linux server built using the Restful API and MVC Controller models. On the server a Flask overlay is adopted on top of a Gunicorn WSGI Server with NginX to handle asynchronous requests and perform load balancing dynamically.
Wu et al. 2018 [81]	A well-designed textile electrode with excellent signal quality and comfort (SQC) plays a significant role in collecting EKG signals. In this study, in order to provide optimization of the SQC, a textile electrode with mesh structure and conductive material comprising silver coated cotton/nylon fiber is investigated. An ADI ADI-based biosensor platform (ADAS1001) has been developed to simplify the task of obtaining and securing quality EKG signals with low power consumption, fast recovery of overhead and high-speed data output.	To reduce power consumption and system complexity, the Microcontroller (STM32) only performs data packaging and retransmission to smart terminals via the Bluetooth 4.2 protocol. The LDO DC-DC regulator with 95 percent conversion efficiency was introduced to decrease power consumption further. In this study, the Keil MDK (Keil uVision5) was used to develop the built-in firmware of the ADAS1000 and STM32 hardware (Microcontroller), which is a comprehensive software development solution for building and debugging embedded applications in microcontrollers.

Table 3
Application development.

Proposed Approach	Application Description	Hardware and Software Description
Hussein et al. 2018 [39]	This work presents a real-time authentication system in IoT based on the use of extracted EKG resources to identify unknown people. This system uses the correlation of predefined RR resources that are stored in the system database and three consecutive RR intervals from the acquired signal.	The stages of preprocessing, RR detection and extraction capabilities are done using the DCT performed on Raspberry PI; While the web-based database and SQLite management application is hosted on the Linux server in Amazon Web Services (AWS).
Penmatsa and Reddy 2016 [33]	The main focus of this proposal is the detection of abnormalities in the heart through a specially designed EKG circuit, and the transmission of data to the smartphone via Bluetooth and subsequently provide real-time monitoring of health care parameters.	In this project, the Arduino-based microcontroller is used as a gateway to communicate with various sensors such as temperature sensor, EKG sensor and pulse oximeter sensor. The microcontroller picks up the sensor data and sends it to the network via the Arduino BT Bluetooth Module.
Zhou et al. 2017 [58]	This system is characterized by the recording and monitoring of mobile HRVs with the reliable collection, transmission, and storage of data from HRV to the cloud.	Through the Android iHRV mobile application, patients can “sign up” into the system and once they log in, they can connect to the usable HRV sensor, Polar H7, via Bluetooth. The mobile application sends the HRV data to the Cloud automatically and when the WEB service based on J2EE Spring framework receives the data analysis module developed with Recess PHP framework. calculates the SDNN value to determine if it is normal, if it is not normal, an alert e-mail is sent to the doctor.
Li et al. 2017 [23]	It proposes an IoT-based heart disease monitoring system for the general health service. This system monitors patients’ physical signals, such as blood pressure, SpO2, and EKG.	An Oximetro to measure SpO2 and a smartphone where the Java-developed APP was installed that performs SpO2 monitoring.
Kirtana and Lokeswari 2017 [106]	The authors propose a low-cost, easy-to-use Remote HRV Monitoring System based on IoT technology for borderline hypertensive patients.	In the proposed system, the HRV parameters are captured using a pulse sensor; the Arduino UNO transmits the patient data to the server. The application server stores a WEB application developed in Java and is using a MySQL database also installed on the application server.
Montalvo et al. 2016 [114]	The prototype includes an alert system that sends messages to the phone application and when using social networks such as Twitter, promptly notifies the attending physician and his or her relatives whenever a critical level in the patient’s body signals is detected.	The prototype includes the Pulse Sensor and Arduino UNO. The proposed Android application is developed on the MIT App Invertor 2 platform and also provides for the management of emergency notifications, this is possible due to the Twitter Developer App linked to the Biotelemetry App.
ElSaadany et al. 2017 [41]	The authors introduce the use of signal processing and machine learning techniques to analyze sensor data for sudden cardiac arrest and prediction of the heart attack.	For this study, a sensory system with a pulse sensor and temperature sensor incorporated with a BLE communication module in an Arduino UNO collects the HR and body temperature using and the predictive analysis is performed in the application installed on a smartphone.
Yoo and Chung 2017 [126]	This study develops a mobile service based on the patient’s stress index that serves as a tool to notify when the patient is facing an emergency or is about to be at risk.	Biological signal measurement clothing used the ZigbeX mote. The development tools in use were EasyTinyOS, Java SE 8u121 JDK and Java COMN2.0.
Jokic et al. 2016 [56]	The authors have developed a mobile app that detects HR using the camera and built-in flash on the smartphone as a receiver of biosignals.	The capture of the biosignals is carried through the camera of a smartphone. The Web platform has been implemented as an App Engine platform application.
Spanó et al. 2016 [63]	This study proposes an EKG remote monitoring system dedicated to non-technical users who require long-term health monitoring in residential environments and integrated into a broader IoT infrastructure.	This work propose a novel integrated circuit board for the capture of EKG signals the designer and the implementation were quite detailed in the article as the firmware developed in the ARM7 MCU.
Vlasov et al. 2017 [110]	The objective of the authors was to develop a cardiography unit that will produce daily monitoring of the patient.	The real-time operating system created by Texas Instruments (TI RTOS) was used as a basis for writing software for the CC2650 microcontroller (MC). As a development environment, Code Composer Studio 7 (CCS 7) was chosen.
Menychtas et al. 2018 [113]	The authors developed an IoT solution using Bluetooth LE to evaluate a proposal oriented to the integration of wearable sensors in mHealth applications.	Presents the methodology that was used for the development of an Android application with the focus on end users, as well as an open solution based on Linux and Raspberry Pi developed in AGILE-IoT (oriented to developers and rapid prototyping).

- Machine learning algorithms can be used to facilitate more accurate diagnosis and even prediction of cardiovascular diseases as demonstrated in the studies [119] that used Apache Mahout for the development of their predictive model for detecting heart disease using logistic regression or, as in [42] in which the decision tree was developed in the WEKA tool using the algorithm J48. However, the poor availability of data in health and the lack of a standard for data collection and sharing can generate erroneous predictions. For instance, despite the development of different pattern recognition algorithms applied in the detection of ECG signals, a functional application has not yet been established.
- The concern with security as methods of traffic or authentication control was emphasized in a few studies. The international protocol HL7, used for electronic data interchange in all health environments, should be evaluated for its adoption in the development of an IoHT project. This is because potentially, all these systems must communicate with each other when they receive new information as demonstrated in the [98]. HL7 specifies a set of standards, guidelines, and methodologies through which various health information systems can communicate with one another.
- Platforms, such as Agile-IoT, geared towards development bring dynamism and great resources to enthusiasts who seek to transform ideas with a focus on IoHT using rapid prototyping. The BonitaBPM platform was used to develop business applications based on processes or workflows used by organizations to improve efficiency in daily operations or for the strategic digital transformation of businesses. This initiative is a valuable alternative for anyone who wishes to develop a project aimed at im-

Table 4
Homologation environment.

Proposed Approach	Application Description	Hardware and Software Description
Manisha et al. 2016 [95]	This work proposes a system to detect heart attacks with the help of different scenarios, for example, monitor heart rate and smart blood pressure.	The project uses the MI BAND 2 smartwatch in conjunction with the monitoring platform developed by the authors using Hadoop, MapReduce, Jaql, Cassandra, Lucene, Hbase, and Mahout.
Singh et al. 2016 [108]	The proposed work focuses on the development of a reliable and low-cost health monitoring system for automotive drivers using EKG electrodes, placed in the seat and the car seat belt.	The proposed system architecture consists of four main parts, (a) Signal acquisition sensors, which include a new EKG electrode configuration, (b) Analog electronic circuit, (c) Signal processing in Digital Domain, (d) Transmission of the signal.
Kumar and Gandhi 2017 [119]	The volume of data generated by the IoT-based health monitoring system is also very high. To overcome this, the authors propose a scalable three-tier architecture to store and process this huge volume of portable sensor data.	Layer 1 concentrates on the data collection of IoT portable sensor devices. Layer 2 uses Apache HBase to store the large volume of wearable IoT sensor data in cloud computing. Layer 3 uses Apache Mahout to develop the predictive model of logistic regression for heart disease. Finally, ROC analysis is performed to identify the most significant clinical parameters for heart disease.
Mohana and H. V. 2015 [123]	The primary purpose of the authors is designing and developing a system that remotely monitors the HR and reproduces music depending on the melody of the heart beats to complement the exercise regimens.	A pulse sensor circuit is designed to get heart rate per minute (bpm). The sensor output is sent to the web server via Arduino UNO, which is also connected to an audio circuit that plays music depending on the patient's HR.
Rizqyawan et al. 2017 [52]	The authors presented the design, development and implementation of their preliminary research on wireless EKG monitoring by using an Android smartphone as a hub to connect it to the server located in the cloud.	There are three main components in this architecture: Bitalino is the component of the sensor that consists of EKG module and motherboard that is responsible for collecting the data and transmit them to the Android smartphone that is the hub using BLE. As the server component, Microsoft Azure was the cloud platform, supported with PHP and CodeIgniter as the backend and Angular server as front-end application.
Yang et al. 2016 [53]	The authors propose a new EKG monitoring method based on IoT techniques. EKG data is collected using a wearable monitoring node and is transmitted directly to the IoT cloud using Wi-Fi. Both HTTP and MQTT protocols are used in the IoT cloud to provide visual and timely EKG data to users.	The EKG sensor AD8232 is the basis of the monitoring node, responsible for collecting EKG data from the human body. The ARM Cortex-M3 is used to process the accumulated EKG signal and send them to the Wi-Fi module which subsequently transmits it to the IoT cloud structure developed by the authors.
Ruiz-Fernández et al. 2017 [60]	This work proposes a model based on the Business Process Management paradigm, along with a group of technologies, techniques, and principles of IT that increase the benefits of the standard. To reach the proposal, the clinical process of hypertension is analyzed with the objective of detecting weaknesses and improving the process. Once the process is examined, an architecture that joins health devices and environmental sensors along with an information system has been developed. In order to test the architecture, a web system connected with health monitors and environment sensors, and with a mobile application was implemented.	In the proposal, the hardware used was: Smartphone, Raspberry PI v3, and sensor BPM180. Already RESTful API, NodeJS, MySQL; Bonita BPM, Apache Cordova framework, Raspbian, Python and AngularJS framework were used in the development of the system to achieve the proposed model.
Haripriya 2016 [141]	The authors propose a patient health monitoring system via IoT and cloud-based processing.	The information of the EKG Sensor, Heart Beat Sensor, Pulse Oximeter Sensor, and LM35 temperature sensor are processed by the microcontroller PIC16F877A, which sends data to the GSM network with the help of the IoT module. A relay is used to switch between the IoT module and the GSM module based on the output voltage of the sensors. The data transmitted by the microcontroller is stored in the cloud for long-term storage and access.

proving a process with the use of IoT for clinical care or even the delivery of a new service model.

- New strategies are being employed in IoT data aggregation and processing. NoSQL databases that are built to scale horizontally are a better alternative for data storage and retrieval than relational DBMSs as they distribute the data by clusters better than Relational DBMS in terms of both data growth and number of users and in the case of IoT in terms of the number of devices acting simultaneously on the data. Processing the large blocks of data that IoT applications collect is often a more appropriate task for a Hadoop cluster, a technology originally developed to help index the Internet, as opposed to standard query calls in a database as demonstrated in studies [95] and [119].
- We found that authors who used the cloud to expose or as part of the computational resource of their experiment, such as in [52], which used Microsoft Azure, or the studies of [44] and [115], which used Amazon Web Services (AWS). Government technology supports initiatives such as Canada's CANARIE, whose mission is to design and provide digital infrastructure to boost its adoption for research, education, and innovation, such as that used in the study of [58] and are timely because initiatives such as these disown investments that often the researchers themselves have to provide for their projects. These platforms, both open source, and proprietary are concerned with addressing the heterogeneity issues related to the cloud and IoT by implementing two middlewares, one on the cloud side and the other on the Things side, as well as by providing an API for application interaction [143].
- Unfortunately, we discovered that independent of the country, the difficulty of evaluating results and consequently validating them with volunteers was the same. Most of the authors chose or unfortunately were only able to evaluate their proposals through the use of medical bases such as MIT-BIH, which generated controlled clinical trials. Depending on the proposed study, such as those in [116] and [48], part of their experiment can be evaluated or even used as a comparative analysis of events. We observed that despite the great potential that IoT can bring to cardiology, as demonstrated in [118], at low cost for ECG

monitoring at the same time for several patients, only a few studies such as [121] and [38] were validated by physicians and were not multicenter collaborative studies, which would allow obtaining a significant mass of data, aiming for a more substantial basis for the acceptance of the results.

4.2. Reference model for online heart monitoring systems

When an experiment proposal is developed, the scope is defined by the definition based on its objectives. The purpose of a goal setting model is to ensure that important aspects of an experiment are defined before planning and execution occur. Often during the study, situations arise that have not been evaluated and might even compromise the continuity of the experiment. Therefore, the development of the project should be accomplished soon after the defining its scope. During the development of the experiment that requires a prototype, the evaluation of cost x benefits that will be captured must be extremely evaluated as, unfortunately, research resources are quite limited.

The following topics should be evaluated for the development of an IoT proposal related to heart monitoring at the time of the study planning: 1) Measured Signals: Identify the bio-signals that should be measured. For example,record the blood pressure for an experiment related to hypertension as the calibration of the same will be paramount to monitoring and subsequently assessing the level of criticality of the volunteer's physical condition [60]; 2) Signal Capture Method: Select the method that will be used to capture the bio-signals punctuated in the experiment proposal; 3) Experimental range: Define the scope of the experiment so that the computational and human resources necessary for the success of the experiment are evaluated; 4) Embedded Platform: After defining the scope of the experiment, it is necessary to identify and subsequently evaluate the computational resources that will be used, including the necessary amount that needs to be invested in the entire project; 5) Application Platform: To utilize the selected computational resources, the use of development platforms will be necessary. An algorithm can initially be created using only logic but for it to be applied practically in the experiment, a programming language must be adopted so that it can be converted into machine code if necessary. In addition to the other features that might be required depending on the proposed scope, such as the adoption of databases or communication platforms to interconnect IoT devices; and 6) Sample Collection: The final step before releasing a health product to the public is to test it on humans. As discussed previously, we identified the difficulty of researchers in evaluating volunteer experiments. Depending on the proposal, the adoption of databases such as MIT-BIH can be used to compare a new feature or method. Currently for analysis, such integration is directly associated with the human being. For instance, in [53], which proposes an IoT-Cloud based ECG monitoring system for Smart Healthcare, several experiments were conducted on a healthy volunteer using the placement of three derivations to verify the reliability and the accuracy of the proposed system.

5. Open issues, learned lessons and future trends

The adoption of IoT devices for health monitoring has encountered great difficulty in acquiring a constant status. For instance, despite the great convenience that a smartwatch brings in being a wrist device, the danger of using equipment like this in places where safety is a negative point can create risks for its wearer. Studies such as [122,130,137] address other resource trends for signal capture in a more discrete manner.

The work described in [122] proposes a wristwatch that is smart, cloud-connected, and wearable and intelligent glasses for discrete and continuous discrete (HR) heart rate monitoring. The glasses consist of a pulse sensor, a microcontroller, and a rechargeable battery. The microcontroller collects analog PPG recordings from the pulse sensor and transmits them to the Android smartphone using the Bluetooth Low Energy (BLE) protocol. Furthermore, [137] proposes a new structure and technical fabrication to realize a flexible multifunctional flat-type integrated patch with acceleration sensor for movement detection, skin temperature sensor, and electrocardiogram (ECG) sensor formed by all printing methods. This is relevant especially when studying a voltage technique and proposing a new manufacturing process and structure using the kirigami concept; all sensors are integrated and demonstrated in a polyethylene terephthalate (PET) film. This study can take the Internet of Things concepts to employ not only the multifunctional health monitoring patch but also sheets of low-cost sensors that can be integrated, for example, into clothing.

Heterogeneous sensors deployed in the environment might prove useful in providing information about behavior and trends in the environment. In [131] a new concept called Urban Heartbeat is presented which uses data captured by various sensors that essentially identify periodic activities in the environment. Urban Heartbeat proposes to serve as a facilitator for new ways of improving health care for society. For this, [130] demonstrates that heart rate can be used not only to differentiate between normal and abnormal trends, helping detect abnormalities, but also predict user behavior or the environment on a significantly early basis. The complexity of time series is used in the approach to heart rate through the Kolmogorov complexity.

In [123], the authors primarily aim to design and develop a system that remotely monitors the heart rate and reproduces music depending on the melody of the heart beats to complement, for example, exercise regimes. Therefore, a pulse sensor circuit is designed to obtain the HR and send it to a server via an Arduino UNO that is also connected to an audio circuit that plays music depending on the patient's HR.

Based on the analysis of selected works, we identified that it might already be a reality to improve medical tools such as the electrocardiogram essentially for the detection and prevention of heart disorders.

However, it is possible to evaluate what additional studies are required for development, safety, and adherence patterns of this new computational technique in the health area.

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