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TOPICAL REVIEW

A Comprehensive Review on Wireless Healthcare Monitoring: System Components

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ABSTRACT Healthcare monitoring systems in hospitals and other health facilities have grown significantly, and portable healthcare monitoring systems using emerging technologies such as Internet of Things (IoT) technologies have aided the advancement of healthcare monitoring systems. Many studies have focused on intelligent healthcare systems in an IoT context to improve components, including wearable sensors and hardware devices, intelligent data collecting and processing, and network connections. Even while these applications are necessary and helpful for enhancing wireless healthcare settings related to monitoring, detection, and diagnostics, it might be challenging to fully understand how IoT characteristics are currently intertwined with its architecture. Accordingly, this work adds to the academic literature by thoroughly reviewing all significant areas of wireless healthcare monitoring system advancements. This research also examines a state-of-the-art healthcare monitoring system component under IoT. One hundred and ninety-four related articles were collected and filtered based on the system components defined. This study includes a thorough review and a list of genuine concerns with novel critical solutions. The study can facilitate academics and practitioners by giving them direction and vital information for future research.

INDEX TERMS Internet of Things, healthcare monitoring, fall detection, sensors technology.

I. INTRODUCTION

In 2020, there were 727 million people aged 65, and the number of older adults worldwide is expected to double over the next three decades, reaching over 1.5 billion in 2050 [1]. The global population aged 65 and up is predicted to rise from 9.3% in 2020 to roughly 16.0% in 2050 [1]. People are now motivated by health awareness and are eager to self-monitor their fundamental health problems. Wearable gadgets are becoming more popular not just in health but also in sports [2]. Therefore, biomedical engineering research is now focusing on creating cost-effective and conveniently accessible solutions for healthcare services aimed at improving both the convenience of use and the comfort of users as life expectancy rises and health expenses rise [3].

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The advances in wireless communication technology, the convenience of deployment, the ubiquity of information, and the low installation cost for healthcare monitoring applications have brought more significant advantages for healthcare monitoring technology systems. In the last decade, a new architecture has arisen in wireless sensor networks (WSNs) by merging two modern technology fields: embedded systems and wireless communications and have been successfully implemented in real-time applications [4]. Different scenarios in WSN-based e-healthcare are summarized below [5]:

1) Daily life supervision - A properly configured WSN can detect the patient's activity and provide valuable feedback, allowing them to better organize their daily lives [6].
2) In-hospital monitoring – The use of WSN technology and the establishment of a wireless body area network

(WBAN) allows for comprehensive care and observation for patients who previously must be kept in the hospital for longer period but instead can be recorded and evaluated regularly by specialists [7]. In such cases, hospitals set up a static node so patients wearing the WSN appliance can stay linked to the monitoring centre while wandering around [8].

3) In-home recovery monitoring following surgery: The WSN technology can provide normal readings of several biological parameters after the patient is sent home, allows for a faster and more accurate diagnosis of heart diseases, and raises the alarm if necessary [9].
4) Sports training: Using wearable devices, the records of athletes' continual observation analyzed, and training is then scheduled accordingly to improve their performance [2].

Falls are unusual activity events that can cause significant health concerns in the elderly and extensive research was done to reduce significant repercussions and harmful effects [10]. Pang et al. [11] discussed a systematic review on the detection of near falls using wearable devices, including accelerometers, gyroscopes, and insole force inducers. Radar and RGB-Depth were utilized due to their contactless and non-intrusive monitoring capabilities [12]. Most studies analyzed a single or few near-fall types by younger adults in controlled laboratory environments and hardly naturally occurring near falls from actual falls or other activities of daily living in older people.

According to [13], assisted living technologies may broadly be classified into three generations. The first-generation technologies consisted of systems and gadgets such as a wearable device with a panic or help button that was assistive only when they received a request or response from the user for help. The second-generation technologies were characterized by their ability to sense when the user needed assistance by tracking health-related, user behaviour-related, and user interaction-related data to trigger alarms to alert caregivers or medical personnel. The third-generation technologies refer to intelligent assistive systems that use a myriad of technologies such as artificial intelligence, machine learning, sensor networks, and their related applications to detect and predict any assistive needs, for instance, in a fall.

The positive influence of the Internet of Things (IoT) in healthcare alters the patient experience while also boosting the quality of care and providing extra health-tracking and security benefits to both patients and healthcare practitioners. The IoT-enabled remote healthcare monitoring (RHM) system connects IoT devices and integrates their data into the patient record system, streamlining data management for enhanced efficiency [14]. The healthcare monitoring system using Healthcare Processing with IoT Surveillance (HPIoTS) was proposed [15] with a reasonable accuracy level of 97% and provided proper graphical outcomes, it is a robust IoT system with advanced capabilities. De Fazio et al. [16] provide a comprehensive overview of innovative IoT sensing systems for monitoring biophysical and psychophysical parameters, all suitable for integration with wearable or portable accessories.

The main contributions of this paper are summarized as follows:

1. The components of the wireless health monitoring system are reviewed and translated to see trends in the study
2. Different types of sensors and wireless communication technology used for wireless health monitoring systems were investigated, and the technology with efficient and low-cost sensors and communication methods was identified.
3. Various fall detection systems were assessed and contrasted in terms of sensor components and their effectiveness.
4. A comparative analysis was highlighted of the current wireless health monitoring system and fall detection system, considering their respective solutions, applicability, and constraints

A. ARCHITECTURE OF THE WIRELESS HEALTHCARE MONITORING SYSTEM

The healthcare monitoring system works according to several stages, as illustrated in Fig 1:

1. Sensor: By using the combination of electronic sensors, the physiological signals of the human body could be converted to electrical signals in the form of quantitative analysis to evaluate the body's health state [17].
2. Data collection and processing: As an interface between all the sensors; to receive the input and provide an appropriate output through microcontroller units (MCU) which are MCU 1 and MCU 2. Both are integrated circuitry designed for embedded systems, combining CPU, memory, and I/O peripherals.
3. Communication: The information was not meant to be kept, so this is where the networking needs to ensure that it will be sent to the doctor in charge.

II. PHYSIOLOGICAL MEASUREMENT AND SENSOR

The human body consists of a natural signal which carries specific information about the physiological system. Physiological vital signs can measure the body's most basic function. Fig 2 represents the trends for types while Fig 3 shows examples of physiological measurement.

Based on the analysis of several previous research, the direction is much more focused on measuring heart rate, with a total of 24 out of 35 articles. The second highest is the temperature measurement with 15 articles, where blood pressure (13 articles), blood oxygen Sp02 (10 articles) and Electrocardiogram (ECG) measurement is about nine articles. ECG is a medical test that records the electrical activity of the heart over time. The rest of the measurements did not get much attention from most of the researchers.

The early development of conventional sensors is rigid, which was not practical to be used for healthcare purposes.

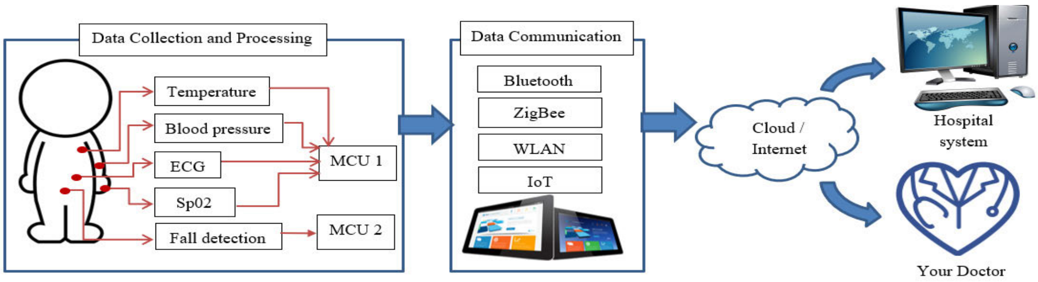


FIGURE 1. Architecture of the healthcare monitoring system.

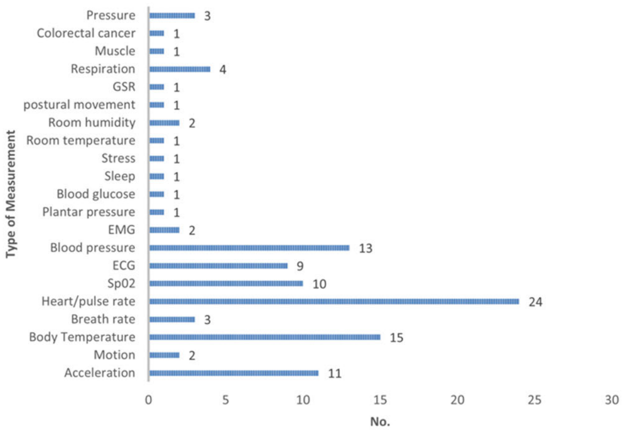


FIGURE 2. Trends for the type of physiological measurement.

At present, an emerging era of sensor technology is swiftly evolving the substrate, resulting in improved control and suitability for healthcare applications. The characteristics of the sensor, which is the advancement of flexible properties, have made the sensor more comfortable and biocompatible to be used in health monitoring applications, as elaborated in the following subsections.

A. BODY TEMPERATURE SENSOR

Body temperature is an indicator of the human wellness body with a temperature of each person varies depending on gender, age, and health status, and somehow following their daily activity. The average normal body temperature can range from 97.6°F (36.4°C) up to 99.6°F (37.3°C). There are various ways to measure the temperature, such as from the mouth, ear, rectum, or forehead [18]. A standard device for measuring body temperature is a thermometer, as shown in Fig 3(a).

Different types of temperature sensors have their applications. The widely used sensor is LM35 [19], [20], [21], [22], [23], [24] due to its low cost and easy setup. A new type of flexible temperature sensor that can be easily attached to the skin was designed [25]. A contactless infrared body temperature sensor MLX-90614 is used in [26]. Fig 4 shows an example of the sensor used for temperature.

B. BLOOD PRESSURE SENSOR

Blood pressure is one of the critical vital signs that can be monitored, as shown in Fig 3(b). The blood pressure sensor measures two specific readings, systolic and diastolic, and measured in millimetres of mercury (mmHg). When assessing blood pressure, several factors might affect the readings, such as age, activity, medications, and the autonomic nervous system [27]. There are different methods for pressure measurement, and one of them is the oscillometric method and the auscultatory method [28], where the detection is based on Korotkoff sound, which comes from the acoustic transducer signal. Another blood pressure sensor is the BP300 sensor, a sensitive, accurate, precise pressure sensor [29]. Another type used for oscillometric is MEMS (micro-electro-mechanical system) sensor. It is a Miniature devices that combine mechanical and electrical components. Fig 5 shows the type of measurement tools for measuring blood pressure.

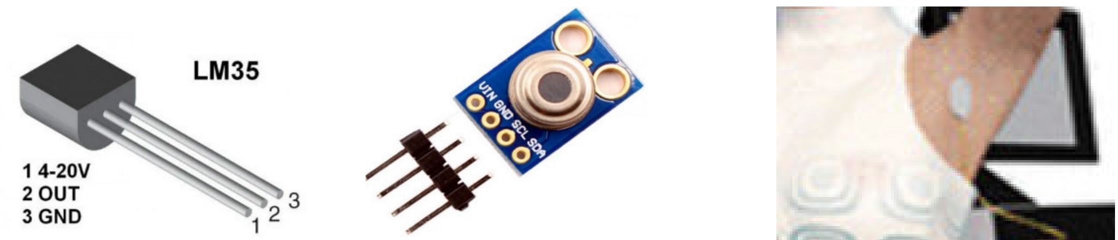
Recently, smartwatches which use an optical sensor can read blood pressure measurements by detecting the changes in blood volume in the tissue and the blood pressure estimation is sent to specific apps for further interpretation [30]. Another design comes with an inflatable strap wristband that will inflate to measure the blood pressure on the wrist [31]. However, these type of smartwatches are not meant to be used as a medical devices or to replace one. Fig 6 shows some of the smartwatches available in the market.

C. PULSE RATE AND OXYGEN SENSOR

Pulse rate is the number of times that the heart beats per i minute (bpm) that can be measured during the contraction of the ventricle of the heart. The average rate for an adult is between 60 to 100 beats per minute and a bit fast, which ranges from 100 to 160 beats per minute for an infant. The average pulse rate decreases as the person get older [32]. Fig 3(c) shows that the pulse rate can easily be measured using hands. The light-dependent resistor (LDR) and piezoelectric sensor are used to monitor the heart rate [33], and it concluded that both sensors are the most suitable and less expensive. Usually, pulse rate and blood oxygen are measured using the same device, the pulse oximeter sensor. Several articles used MAX30100 and MAX30102 for pulse oximetry and heart rate monitor sensors [20], [34] and showed readings in the range of 95%, which is within the acceptable clinical

a) Thermometer [48]
b) Blood pressure [49]
c) Pulse rate [50]
d) ECG [51]
e) Blood oxygen ($Sp0^2$) [52]
f) Fall detection [53]

FIGURE 3. Physiological measurement.



a) LM35 sensor [54]
b) Non-contact IR temperature sensor [55]
c) FlexibleTemperature sensor [25]

FIGURE 4. Example of temperature sensor.

a) Auscultatory method [56]
b) Oscillometric method [57]

FIGURE 5. Blood pressure measurement.

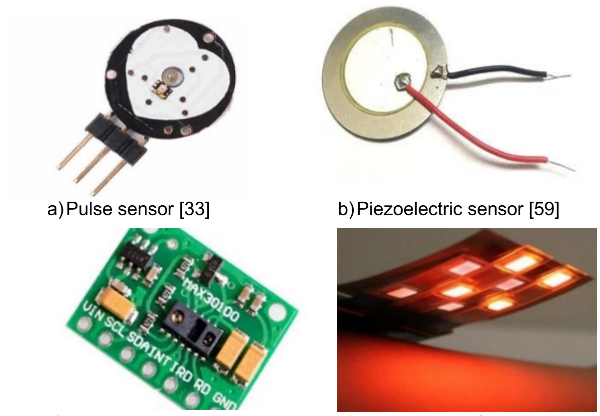
range. The light absorption of red and infrared light of a pulse oximeter measures the oxygen saturation of the haemoglobin in the blood [35]. Most pulse oximeters need to be wearable, usually on a fingertip, to measure the blood oxygen level [36], [37], [38]. Fig 7 represents the type of pulse rate and blood oxygen sensor.

D. ELECTROCARDIOGRAM (ECG)

Healthcare professionals have used different types of ECG lead positioning, ranging from 3 lead up to 12 lead electrode placements. Fig 3(d) shows the example of an electrode lead positioning for three leads. Electrodes are small patches of plastic material used to detect the electrical changes in the cardiac and are placed at a specific point on the chest, arms, or legs [39]. A conventionally wet electrode is generally made of silver/silver chloride (Ag/AgCl) material and must be used with an electrolytic gel as a conductor between the skin and electrode [40], [41]. The dry electrode is a silver-coated plate that can be operated without the electrolytic gel, and Wang and Fang [42] used dry electrodes to measure real-time ECG placed on a smartphone case. Fatih [43] used three positive, negative, and neutral leads designed to be used with the

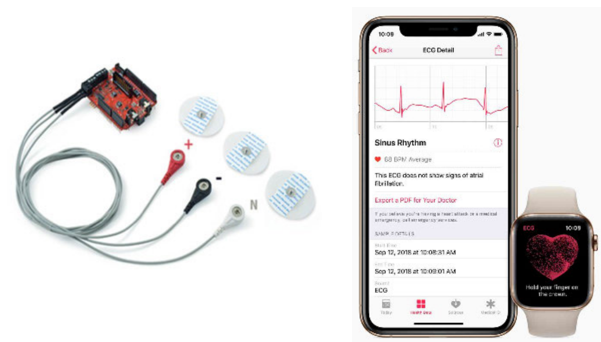
a) Blood pressure smartwatch using optical sensor [30] b) Blood pressure smartwatch comes with inflatable strap [58]

FIGURE 6. Examples of smartwatch.



a) Pulse sensor [33] b) Piezoelectric sensor [59] c) MAX30100 [60] d) Printed Blood Oxygen sensor [25]

FIGURE 7. Pulse rate and blood oxygen sensor.



a) Traditional ECG monitoring using 3leads electrode [43] b) ECG monitoring using Smartwatch [61]

FIGURE 8. ECG monitoring sensor.

e-Health Sensor Platform. Fig 8 shows the traditional and modern monitoring of ECG measurements.

E. BLOOD OXYGEN (SP02) FALL DETECTION

The normal range of the oxygen-saturated blood of healthy persons should be 96% up to 100% [44], and those lower than that range will show signs such as shortness of breath or chest pain. Blood oxygen can be measured using the pulse oximeter, which is usually reported as Sp02 (saturation of peripheral oxygen). Fig 3(e) shows the pulse oximeter used to measure blood oxygen saturation.

FIGURE 9. Fall detection sensor [62].

F. FALL DETECTION

Fall detection is one of the technologies important as a medical alert system that can alert other parties when someone has an emergency. Fall detection works in an instant, where when the detection is triggered, it will automatically send the signal to request help [45]. The fall detection sensor, the accelerometer, measures the acceleration by calculating the changes in motion and body position in three perpendicular data (x, y and z axes) and determining whether it is a fall or not. Janat and Haque [46] added a particular checkpoint that must all be satisfied and evaluated as fall. Most fall detection sensor is wearable and designed according to [45], the steadiest position to reflect the motion of the human body is at the waist. It is also found that the sensor position at the waist and wrist has the highest accuracy compared to the calf, chest, and thigh sensor positions [47]. Fig 3(f) shows an example of fall detection devices. Fig 9 represents the example of sensors positioning for fall detection.

Thirty-five papers have been selected for further review on wireless healthcare monitoring systems and classified in Table 1 according to the measurement, sensor, and communication types used. The last column of the table highlights the findings of each paper. Table 1 serves as a preliminary categorization based on measurement, sensor, and

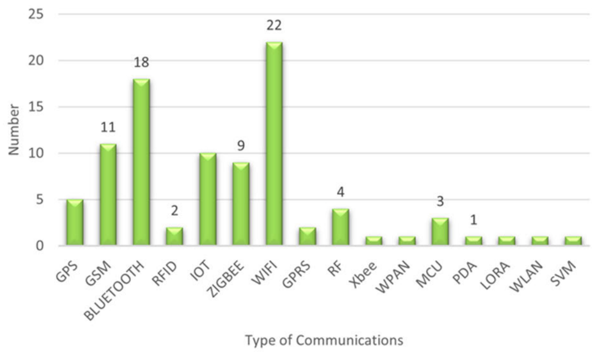


FIGURE 10. Types of communication used by researchers in Table 1.

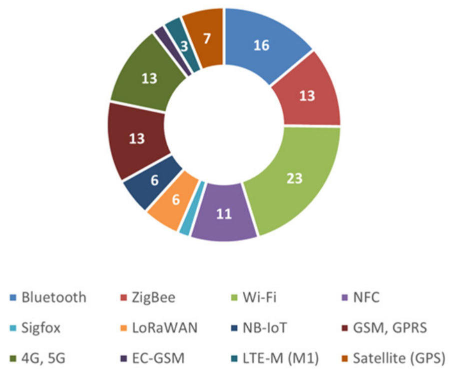


FIGURE 11. Types of communication used by researchers in Table 2.

communication types. The subsequent focus on fall detection is explicitly mentioned in Table 2, where a detailed examination of measurement techniques, patterns, and sensor types related to fall detection is presented. Both tables interpret the pattern trends for the measurement sensor and the types of sensors as well as the communication types used. In addition, Table 2 is on reviewing fall detection aspects within wireless healthcare monitoring systems.

Fig 10 summarizes the type of communication technologies used by researchers on papers summarized in Table 1 while Fig 11 summarises papers summarized in Table 2.

1) FALL DETECTION: SINGLE SENSOR

Researchers in [45] deploy a single accelerometer sensor in their work. They emphasize resource usage; thus, a simple and reliable threshold detection algorithm is deployed in their works designed adequately for outdoor applications. The algorithm developed does not require the axes of the accelerometer to be in a specific mounting orientation. A study in [97] works on improving the noise from the sole sensor's data using confidence intervals and techniques of Leaving-One-Out before applying k-Nearest Neighbors (KNN) is a machine learning algorithm for classification and regression tasks. Wi-Fi network is used as a transmission medium alert for messages. Work in [84] opted to test their fall detector by deploying a threshold based Kalman filter method using non-linear metric features, which achieved up to 99.4% accuracy on the largest dataset freely available in the literature (SisFall) which is the Fall Detection Dataset - Collection of sensor data for studying fall detection algorithms. A real-life test leaves an excellent option for future enhancement of the device and research such that the false positive could be reduced to differentiate better fall and high-acceleration activity of daily living (ADLs). ADLs are the basic tasks people do every day, like eating, dressing, and bathing. They are important for independence and are used to check a person's ability to care for themselves. They are often used in healthcare and rehabilitation settings to assess an individual's physical and cognitive abilities and determine their need for assistance or support. The authors also claimed that their device satisfies the single-charged full-day use concerning a simple classification method, less active-time sampling rate of 25 Hz, and single-use sensor. In a slightly different approach, researchers in [98] use gyroscopes instead of accelerometers in their recognition of fall events. Nevertheless, they opted for the application of low complexity but advanced detection algorithm of machine learning and meticulous pre-processing of data, resulting in the proposed method effectively distinguishing fall events from other daily life activities with credible performance parameters: Accuracy of 99.52%, Precision of 0.993, Recall of 0.995, and F1-score of 0.994.

Researchers in [47] proposed a framework for edge computing to process data for real-time analysis. They even deploy high-end deep learning of fall classification and public datasets for training, while validation is by experiment using the proposed sensor device, which includes optimum sampling frequency and ideal sensor placements on the subject. Another IoT-based example [92] works on a highly versatile fall detection system by allowing any Wi-Fi-enabled devices embedded with accelerometers and specific modules to act as fall monitors. Data from these devices are sent to the multi-threaded server, which hosts a pre-trained machine learning model to analyze data and notifies devices of the results, user's location, and alert for fall detection. To better the accuracy performance, [95] presents a personalized fall detection system with a deep neural network combined with ensemble techniques as a detection algorithm. Based on the real-world experiment, the model significantly outperformed the generic fall detection model, especially regarding precision. In a study by [84], researchers focused on acquiring data from a single type. However, they conducted multiple experiments on this framework and demonstrated that multi-sensor fusion leads to better performance of detection systems.

2) FALL DETECTION: MULTI-SENSOR

In the early stage of multi-sensors data acquisition, the focus of [23] is on the wireless transmission feasibility of the data to a personal computer or workstation. In this case, a comparison between ZigBee and Bluetooth modules is discussed, eventually ending with ZigBee for lower power consumption. Utilizing sensors fusion advantages,

TABLE 1. Review of measurement of the sensors.

No.	Paper Title	Measurement	Type of Sensor	Communication	Outcome
1.	Real-time wireless health monitoring system, 2014. [19]	-Temperature -Heart rate and blood oxygen (Sp02) -Breath rate	-LM35 -Finger photo-plethysmograph (PPG) (red infrared light absorption) -50k negative temperature coefficient thermistor	XBee interfaced with Arduino, LabVIEW and GUI	Advantages: The breath rate sensor works efficiently for up to 18 breathe/min Disadvantages: Inaccurate results occur when the breath rate is more than 18.
2.	Patient Health Monitoring System using IoT, 2021. [20]	-Temperature -ECG -Pulse oximeter (SPO2) -Blood pressure	-LM35 -AD8232 -MAX30100 -Blood pressure sensor (oscillometric method)	ESP32 microcontroller, Global System for Mobile Communications (GSM), ThinkSpeak (cloud-based IoT)	Advantages: ESP32 has more memory capacity than Arduino
3.	Wearable IoT enabled real-time health monitoring system, 2018. [21]	Heartbeat(rate), temperature, Blood pressure	-Wearable heartbeat sensor, temperature sensor LM35, Blood pressure sensor	WISE cloud through Radio Frequency Identification (RFID) reader which connected to the Arduino	-Enable real-time monitoring for the patients. However, a few issues remain with developing a cost-effective wearable IoT, ensuring scalability, robustness, security privacy, etc.
4.	Development of smart healthcare monitoring system in IoT environment, 2020. [22]	Heartbeat, temperature, C0	-Heartbeat sensor, temperature sensor (LM35), Room temperature sensor (DHT11), CO sensor (MQ-9), CO2 sensor (MQ-135)	ESP32 Module, ThingSpeak, Wi-Fi	-ESP32 has a built-in Wi-Fi module -Error rate is not more than 5% which is acceptable.
5.	Wireless patient health monitoring system, 2013. [24]	Heartbeat, temperature	Op-Amp LM358, temperature sensor LM35	ZigBee	Findings: LM35 measures temperature more accurately than the thermistor and generates a higher output voltage than thermocouples. Zigbee is more straightforward and less expensive.
6.	Flexible and wearable healthcare sensors for visual reality health monitoring, 2019. [25]	Electroencephalogram (EEG), Heart Rate, Temperature, ECG, Breath Rate, Blood Pressure, Pulse Rate, Electromyography (EMG), Plantar pressure	A flexible sensor attached to the skin (Blood oxygen, Wireless sweat, Blood and pressure, Temperature, Breathalyzer, Electrochemical sweat, ECG chest band heart rate and diseases sensor).	Bluetooth	Advantages: Flexible electronics are more comfortable, biocompatible, energy-saving, and portable Disadvantages: The flexible healthcare sensor must be worn on a different part of the body, making diagnosis difficult.
7.	Detailed research on human health monitoring system based on IoT, 2021. [29]	Pulse, Body temperature, heart rate, Blood pressure	-The impulse data sensor of the ROHM semiconductor -Temperature sensor - BP300 blood pressure sensor	Wireless communication	Findings: The temperature and pulse rate values are accurate and stable.
8.	Heart (Pulse rate) Monitoring using Pulse Rate Sensor, Piezoelectric sensor and NOdeMCU, 2021. [33]	-Monitor heart (pulse rate), -Blood pressure	-Pulse rate sensor (Light-dependent Resistor LDR) -Piezoelectric sensor (Pressure)	WiFi module NodeMCU sent to Arduino	Findings: Provides accurate monitoring of patients at any location, easy to use and less expensive
9.	Design and implementation of an Sp02-based sensor for heart monitoring using an android application, 2019. [34]	Sp02, Heart rate, body temperature	Sp02 sensor (PPG signal), Heart sensor (MAX30102), human body temperature sensor	Arduino, Printed Circuit Board, Liquid Crystal Display (LCD), Bluetooth module	Advantages: Standard error between 1-2% both for heart rate and Sp02. The proposed device showed readings in the range of 95%, within the acceptable clinical range. Disadvantages: time is taken to measure 20-25 sec compared with the available device in the market

TABLE 1. ***(Continued.)*** **Review of measurement of the sensors.**

10.	Internet of things: Low cost and wearable Sp02 device for health monitoring, 2018. [36]	Sp02 and heart rate	Finger sensor, oximeter module	MCU node, Wi-Fi connection with a bandwidth of 10 Mbps	Findings: The error rate is ±2.8 BPM for heart rate and Sp02is ±1.5%. Data sent to the internet can be accessed online and in real-time.
11.	Wireless heart rate and oxygen saturation monitor, 2019. [37]	Sp02, Heart rate	Sp02 sensor (PPG signal) (wearable on finger), Peak detection algorithm (PDA) is a computational method used to identify and locate the peaks or local maxima in a dataset and Autocorrelation function (ACF).	Wi-Fi	Findings: A wireless heart rate and oxygen saturation using a low-cost microcontroller was developed with accurate results
12.	Wide and High Accessible Mobile Healthcare System in IP-based WSN, 2013. [38]	ECG, PPG (Sp02)	-ECG Sensor, PPG sensor (wearable)	IPv6 over low-power wireless personal area networks (6LoWPAN) which is a short-range wireless network for device interconnectivity.	Findings: The android application is easy to apply on mobile devices such as PC, tablets, etc.
13.	Developing Residential Wireless Sensor Networks for ECG Healthcare Monitoring, 2017[39].	ECG	-3 leads ECG sensor attached to the lower/upper chest by acquiring the heart's electrical activity between electrode pairs.	ZigBee	Findings: Provide low power connectivity and low cost for equipment that requires long battery life. However, it does not necessitate high data transfer rates as those empowered by Bluetooth.
14.	A wireless health monitoring system using mobile phone accessories, 2017[42].	ECG, Heart Rate, Respiration (Detection using a touch of a fingertip at the phone case)	Passive Infrared Sensor (PIR) Sensor, Electric Potential Integrated Circuit (EPIC) Sensor, ECG Sensor	Bluetooth 4.0 BLE (Bluetooth Low Energy) using RFduino	Findings: More complex and secured than usual Bluetooth technology. Low power and compatible with both android and iPhone operating system platforms. However, the pressure and resistance affect the ECG measurement.
15.	Review wireless patient monitoring system & its performance,2016. [63]	Temperature, Heartbeat	-Temperature sensor -Heartbeat sensor (finger clip)	PIC microcontroller is a programmable Interface Controller. It is a microcontroller with versatile applications in embedded systems, microcontroller, GSM, ZigBee,	Findings: PIC microcontroller offers high performance and low power consumption. The system provides safe and accurate monitoring and freedom of movement.
16.	Wireless ECG and cardiac monitoring systems: State of the art, available commercial devices and valuable electronic components, 2021. [3]	-ECG	-A silicon microneedle electrode was proposed	Wi-Fi, Bluetooth	Findings: BLE is advantageous in terms of power consumption; Wi-Fi and Bluetooth can suffer from instability and packet loss transmission
17.	A Bluetooth low energy approach for monitoring Electrocardiography and Respiration, 2013. [64]	-ECG -Respiration Temp	-Five lead wires were used for ECG, including the right leg drive. -Respiration shares two horizontal electrodes (LL, RA) on the chest.	BLE 112	Findings: Saves as much as 75% power consumption and is portable. However, it lacks compatibility compared to standard Bluetooth.
18.	IoT Based Health Monitoring System, 2020. [65]	Heartbeat (Heart rate), Blood pressure	Heartbeat sensor, LM37 temperature sensor	GSM, IoT	Findings: The stored data can be easily viewed through the desktop or any android device.
19.	Smart health monitoring system based on WSN, 2016. [66]	Body temperature, pulse rate	Temperature sensor, heart rate sensor	Zigbee	Findings: Zigbee consumes less power, long range, low data rate, and low transmission delay. Compact and energy efficient WSN
20.	The use of smartwatches to monitor heart rates in elderly people: A	Heart rate	Using smartwatches	Bluetooth, Mobile app, ZigBee	Findings: Future works propose a knowledge-based system combined with a rule-based

TABLE 1. ***(Continued.)*** **Review of measurement of the sensors.**

	complementary approach, 2016.[67]				system that will provide a proactive response when an abnormal heart rate occurs.
21.	Development of a wireless health monitoring system for measuring core body temperature from the back of the body, 2019. [68]	Temperature	Semiconductor-micro-temperature sensor with maximum accuracy of ±0.3°c (wearable on the back of the body)	MCU, RF transmitter, midi logger GF820	Findings: Small sensor measurement errors contribute to accurate skin temperature measurements with low power consumption. A lifelong battery approximates up to 40 hours.
22.	Heart rate and oxygen saturation monitoring with a new wearable wireless device in the intensive care unit. Pilot comparison trial, 2020. [69]	Cardiac, Sp02	SmartCardia (wearable wireless biosensor patch)	Bluetooth	Advantages: The result shows good quality and maintains adequate skin contact by reapplication and repositioning. Disadvantages: Small number of patients with the poor recording quality.
23.	IoT-based health monitoring system, 2020. [70]	Heartbeat, Sp02, temperature, and humidity of the room	Temperature sensor , Heartbeat sensor (photo phlethysmography), Humidity sensor (hygrometer) (embedded in patients' body)	ZigBee, wireless local area network	Findings: The system sends patients' data using the IoT platform.
24.	A hospital healthcare monitoring system using WSN, 2013. [71]	Heart rate, blood pressure	Motion detection Accelerometer, blood pressure and heart rate sensor, Movement of the fetal	General Packet Radio Service (GPRS), GSM	Findings: The proposed wireless body sensor network (WBSN) has better performance than the existing WBSN systems.
25.	Wearable sensors for remote healthcare monitoring system, 2012. [72]	Blood pressure, Sp02, muscle, cardiac	WBAN, Sensing chip, Medical super sensor (MSS)	ZigBee	Advantages: WBAN consists of smaller nodes and less space covered, and fewer opportunities for redundancy Disadvantages: Wireless devices face challenges because wireless is slower than wired devices.
26	Recent Advances on IoT-Assisted Wearable Sensor Systems for Healthcare Monitoring, 2021[73]	- Stroke Rehabilitation - Blood Glucose - Cardiac - Respiration - Sleep, - Blood Pressure - Stress - Alzheimer's Disease (AD)	-Glucose sensor, Heart rate sensor, Smart insole shoes - myRIO 1900, ECG sensor, NI LabVIEW, EKG sensor - Blood pressure sensor	- Bluetooth, WiFi, Zig Bee - Arduino Uno, Bluetooth 4 BLE module, 16 × 2 LCD, R pi, and WiFi/4G Long Term Evolution (LTE)-GPS, three-axis accelerometer - Mobile apps - MQTT	Findings: Real-time monitoring and the capacity to predict potential anomalies and severe repercussions in at-risk patients.
27	A priority-aware lightweight, secure sensing model for body area networks with clinical healthcare applications in the Internet of Things, 2020 [74]	- Position, postural movement, temperature, quality service, cross-layered	- Eye-tracking sensor, pulse sensor, breathing rate sensor, motion sensor, the sink node	- Radio model and single-chip low-power transceiver of Nordic nRF 2401A, sensing model, cloud	Findings: Make it easier for Body Area Networks (BANs) to understand the newly established protocol-based routing schemes and present a sensing model that addresses security and energy consumption concerns
28	Do-Care: A dynamic ontology reasoning-based healthcare monitoring system, 2021 [75]	- Body temperature, heart rate, blood pressure, respiratory,	- Semantic Sensors Network (SSN) / Sensor, Observation, Sample, and Actuator Ontology (SOAS) ontology sensor	- Mobile app, Personal Digital Assistant (PDA)	Findings: A Semantic Web Rule Language or SWRL rule-based reasoning engine and subjective and objective knowledge bases are used to customize a decision-making strategy. The system's efficiency, ontology, and reasoning engine are all tested.
29	Continuous health monitoring of sportsperson using IoT	- Heart rate	- Pulse rate sensor, using a smart device	- Mobile app, WiFi/4G, Bluetooth	Findings: The sportsperson's health is collected using Internet of Things (IoT) based wearable

TABLE 1. ***(Continued.)*** **Review of measurement of the sensors.**

	devices based wearable technology, 2020 [76]				sensors. The system uses using Ensemble Bayesian deep classifier (EBDC) method.
30	A Rigid-Flex Wearable Health Monitoring Sensor Patch for IoT-Connected Healthcare Applications, 2020 [77]	- ECG - PPG - Body temperature - Blood pressure - Heart rate	- ECG and PPG sensors	- Bluetooth low-energy (BLE), mobile gateway (mobile phones), fixed gateway (portable computers), cloud	Findings: The entire platform for IoT-connected healthcare applications can be used productively as commercial reference medical equipment.
31	IoT-based wearable sensor for diseases prediction and symptom analysis in the healthcare sector, 2020 [78]	- Colorectal cancer	- Aptasensors, sensing model	- Mobile phones, WiFi/4G, cloud	Findings: Neuro-fuzzy-based algorithms have been proposed to predict colorectal cancer in patients
32	Smart Face Mask with an Integrated Heat Flux Sensor for Fast and Remote People's Healthcare Monitoring, 2021 [79]	- Body temperature, breathing rate	- Dual heat flux sensor, airflow sensor, temperature sensor, dual heat flow sensor	- Long-range (LoRa) backscattering, MAX 30205 integrated circuit, Bluetooth, WiFi, mobile app, cloud	Findings: Low cost, Estimate of the core temperature, breathing rate measurements. Commercial LoRa transceivers are used in the system.
33	Automated Internet of Medical Things (IoMT) Based Healthcare Monitoring System, 2021 [80]	- Heart rate, pulse rate	- Wireless sensor network, pulse oximeter sensor, body temperature sensor, heart rate sensor, ECG	- WiFi, web system	Findings: The study implemented Chi-square automatic interaction detection or CHAID algorithms to evaluate the accuracy of the information. The information from the sensor to the physicians has increased the ECG sensor's prediction.
34	Analysis and monitoring of IoT-assisted human physiological galvanic skin response factor for smart e-healthcare, 2019 [81]	- Galvanic skin response (GSR), respiratory	- Copper film (acting sensor), GSR sensor	Bluetooth, smartphone, ATTiny 85 microcontroller, LM3 58 amplifier, OPA4336E A, CR2032 coin battery, MakerPlot, Arduino,, Fritzing and MIT App Inventor 2, Pyralux	Findings: Hands-on usage is required for the GSR system. Human physiological instabilities might be considered when determining the user's maximum strength or endurance level. With the planned GSR system, there is enough room and potential for it to be developed and expanded beyond the goals and expectations.
35	The modelling and simulation of IoT system in healthcare applications, 2021 [82]	- Blood pressure and heart rate - Stroke rehabilitation	- PPG and ECG sensors - EMG signal	- Mobile devices, WiFi, rechargeable power supply, microcontroll er - Smart wearable armband device, 3D printed robot, WiFi, Arduino Mega 2560, servo motor	Findings: The device's design has been simplified and made more usable thanks to its interaction with a smartphone. Results reveal that the intelligent wearable wristband is straightforward to use without needing the physician's technical expertise or assistance.

[99] claims single-use accelerometers tend to mistake some ADLs as falls. Regarding this, the Euler angle is performed with their threshold-based detection to enhance their detection accuracy further. The work also verifies the best body location to place the sensors and obtains the best acceleration threshold for accurate fall detection. Data transmission to the android app on a smartphone using Bluetooth communication, the app will emit an alarm sound and issue a call to the emergency contact upon fall detection.

Regarding user acceptability issues, work by [100] comes out with smart shoes equipped with force sensors and accelerometers. Fall detection works independently for each shoe, and by combining both sensors' data, features are calculated to achieve the final output. The detailed construction of the hardware is meant for user comfort without noticing the presence of the system module. Interestingly the module is even equipped with a Bluetooth transmission module to transmit the data to the microcontroller Raspberry pi 3 for data processing. The health parameters are transferred using aRRFID Technology for tracking and identifying objects using radio waves signal to a data acquisition spot for both health and fall data to be analyzed before transmitting the results to the server via Bluetooth. In [46], thresholds are used as a detection algorithm with several sensors as input parameters.

TABLE 2. Review of fall detection.

NO.	Paper Title	Type of Sensor	Location of the sensor	Communication	End-user	Outcome
1.	Development of a wearable sensor-based fall detection system, 2015. [45]	A single triaxial accelerometer detects acceleration analysis,	Wearable device - Waist	GPS, GSM, Virtual Machine	Send request help to caregivers	The single triaxial accelerometer is enough for fall detection because sufficient information can be extracted. It uses fewer resources and power consumption.
2.	IoT-based health monitoring & fall detection system, 2019. [46]	Pressure, temperature, and humidity sensor combined with flexible silicon IC on (smartwatch)	Smartwatch (Wrist)	RFID, Bluetooth, GSM, IoT	Send to receiving device	The proposed system will replace the flexible printed circuit with printed stretchable metal interconnect on a low-cost platform. The system will be more budget-friendly and also user-friendly.
3.	A real-time patient monitoring framework for fall detection, 2019. [47]	MetaMotionR sensor	Wrist, Chest, Side waist, Calf, Thigh	Bluetooth, wireless communications	Send data to the cloud	Affordable and adaptable system. LSTM (Long Short-Term Memory) is a type of recurrent neural network architecture for sequential data and its model detect 99% accuracy. The proposed framework for fall detection can identify falls 95.8% of the time.
4.	A ZigBee-based patient health monitoring system, 2013. [23]	Temperature sensor (LM35), heart rate sensor (LED and IR), MEMS sensor (MMA7260QT), Saline level sensor (555 timer and TSOP1738 IR sensor)	Fitted into the wrist strap	ZigBee, RS232, GSM	Message to caretakers	Advantages: ZigBee has low power consumption, Low power operational amplifier Disadvantages: Bluetooth is better for transmission rate
5.	Physiological parameter measurement using wearable sensors and cloud computing, 2020. [83]	Three-axis accelerometers (ADXL 335), wearable temperature sensors include thermistor (LM393), Pulse oximeter, ECG signal (three lead ring-type electrodes)	Placed on chest	GSM, GPS (Global Positioning System) is a satellite navigation system for determining precise location, ESP8266 Wi-Fi module, ThingSpeak(IoT), LabVIEW	Short Message Service (SMS) is sent to the respected person	Low-cost Wi-Fi module, Thermistor has low operating voltage, low power consumption and compactness, ThingSpeak has broad community support.
6.	Real-Life/Real-Time Elderly Fall Detection with a Triaxial Accelerometer, 2018.[84]	Triaxial Accelerometer, Kinets MKL25Z128VLK4 microcontroller with an ADXL345 accelerometer	Waist	GPRS	Send SMS	The device accomplishes the full-day single-charge requirement for being feasible under real-life use. This approach is more efficient than SVM or neural networks. Advantages: energy efficient when sampling at 25 Hz instead of 50-100 Hz

TABLE 2. ***(Continued.)*** **Review of fall detection.**

7.	A Feasibility Study of the Use of Smartwatches in Wearable Fall Detection Systems, 2021. [85]	Inertial sensors MPU9250, six IMU (Inertial Measurement Unit) is a sensor package measuring orientation, acceleration, and rotation, which enabled wireless wearable motes, the sampling rate of 10 ms (100 Hz frequency) to a maximum of 2550 ms (0.39 Hz),	Waist	GPS, Bluetooth, Wi-Fi	Sent SMS to user	An adequate sampling rate between 20 and 40 Hz is enough
8.	Influence of the Antenna Orientation on Wi-Fi-Based Fall Detection Systems, 2021. [86]	Antenna, Doppler spectrum	Room surrounding	WiFi	Send alert message	Accuracy of horizontal polarization: 92% Accuracy of vertical polarization: 50%
9.	Innovative Head-Mounted System Based on Inertial Sensors and Magnetometer for Detecting Falling Movements, 2020. [87]	16-bit Triaxial accelerometer, 16-bit gyroscope (MPU6050), and 12-bit magnetometer (HMC5883L), Madgwick's filter	Worn on the head (eyeglasses)	Wi-Fi, 8-bit MCU	Notify emergency contact	The proposed system can achieve an accuracy of 97.75%, a sensitivity of 96.67%, and a specificity of 98.27%.
10.	Wearable Feet Pressure Sensor for Human Gait and Falling Diagnosis, 2021. [88]	Six piezoelectric pressure sensors	Shoe lining	ESP32, 2.4GHz Wi-Fi	Send data to tablets or smartphones	Accuracy can reach up to 94%
11.	Fall Detection Using Deep Learning in Range-Doppler Radars, 2018 [89]	Range-Doppler radar	Installation of motion radar in the area of interest	radio-frequency electromagnetic signal	Not stated	Deep learning detection incorporating range-Doppler radar Reduce false alarm: fuse information from time-frequency and range domains.
12.	IoT-based health monitoring & fall detection system, 2019. [46]	Pressure, temperature, and humidity sensor combined with flexible silicon IC on	Smartwatch (Wrist)	RFID, Bluetooth, GSM	-Elderly -Send SMS and email to receiving device	-The proposed system will replace the flexible printed circuit with printed stretchable metal interconnect on a low-cost platform. -the system will be more budget-friendly and also user-friendly.
13.	A real-time patient monitoring framework for fall detection, 2019. [47]	MetaMotionR sensor	Wrist, Chest, Side waist, Calf, Thigh	TensorFlow, LSTM module, machine learning (MobiAct)	Send data to the cloud	Optimum frequency (waist): 50 Hz Ideal sensor placement (fix sampling frequency: waist LSTM models detect 99% accuracy. The proposed fall detection framework can identify falls 95.8% of the time.
14.	Fall detection and human activity classification using wearable sensors and compressed sensing, 2019 [90]	Accelerometer and gyroscope	Chest	Bluetooth	Call emergency	Detect all fall events as one type of fall but detect various ADLs activities specifically. Applied comprehensive sensing method Accuracy: 99.8%
15.	Physiological parameter measurement using wearable sensors and cloud computing, 2020. [83]	Three-axis accelerometers (ADXL 335), wearable temperature sensors include thermistor (LM393), Pulse oximeter, ECG	Accelerometer is placed on the chest. A temperature sensor is placed on the wrist.	GSM, GPS, ESP8266 Wi-Fi module, ThingSpeak (IoT), LabVIEW	SMS is sent to the respected person	Low-cost and compact Wi-Fi module, Low operating voltage thermistor ThingSpeak has broad community support.

TABLE 2. ***(Continued.)*** **Review of fall detection.**

		signal (three lead ring-type electrodes)				
16.	A WiFi-Based Smart Home Fall Detection System Using Recurrent Neural Network, 2020 [91]	Motion sensor	Motion interference with a pair of commercial WiFi devices installed in residential units	Wi-Fi network	Mobile App or management web platform	Employ deep learning; RNN (Recurrent Neural Network) is a neural network designed for sequence data analysis as fall detection algorithm. Real-time data analysed is uploaded to the proxy server and obtained systematic data interpretation. Advantage: passive device-free detection. Alert personnel of monitored subject fall behaviour.
17.	An IoT-based device-type invariant fall detection system, 2020 [92]	Accelerometer	Users' left or right pant pocket	Wi-Fi, GPS, GSM	Buzzer alarm and SMS	Client-server architecture: Allow detection from any IoT device that can interface modules: accelerometer, buzzer, GPS and GSM Multithreading server: fast computation output Performance: 99.7% accuracy, 96.3% sensitivity, and 99.6%
18.	Fall detection in older adults with mobile IoT devices and machine learning in the cloud and on edge, 2020 [93]	Accelerometer and gyroscope	Smartphone	Wi-Fi network	Auto-call an emergency service	Present two alternative locations of fall detection (the Cloud-based and the Edge-based) It mitigates significant data challenges by operating scalable computing and storage resources for the growing number of monitored people.
19.	Fall Monitoring for the Elderly Using Wearable Inertial Measurement Sensors on Eyeglasses, 2020 [94]	Accelerometer and gyroscope	IMU embedded eyeglasses	Wi-Fi network	-Elderly Email and SMS	Monitor the sudden rise in acceleration and the user's head orientation to detect falls. Implement complementary filters to improve data accuracy. Accuracy: 95.44% in identifying falling and non-falling actions
20.	Personalized Fall Detection System, 2020 [95]	Triaxial Accelerometer	Smartwatch	Bluetooth	Alert on smartphone App	The scarcity of wrist-worn devices is mitigated by collecting personalized false positive fall data samples from individual users and training in a generic deep learning ensemble model to optimise for high recall and enhanced model precision. An innovative method of detecting falls and increasing the relevance of using the wrist-worn device as a fall detection system
21.	Wearable Computing with Distributed Deep Learning Hierarchy: A Study of Fall Detection, 2020 [96]	Accelerometer and gyroscope (smartphone, smartwatch), and	Waist, wrist, feet	Bluetooth, text-based protocol: Redis Serialization Protocol	Cloud server to smartphone: RESP	The system makes use of both smartphone and cloud resources to protect local data privacy.

TABLE 2. ***(Continued.)*** **Review of fall detection.**

		pressure sensor (smart insoles)		(RESP)		The use of computational resources on the cloud server reduces the computational overhead on smartphones.
22.	A Feasibility Study of the Use of Smartwatches in Wearable Fall Detection Systems, 2021. [85]	Inertial sensors MPU9250, six IMU-enabled wireless wearable motes, the sampling rate of 10 ms (100 Hz frequency) to a maximum of 2550 ms (0.39 Hz),	Waist	GPS, Bluetooth, Wi-Fi	Sent SMS to user	An adequate sampling rate between 20 and 40 Hz is enough

Furthermore, to complement the threshold method, the work added a series of checkpoints to be satisfied by the analyzed data before deciding on the output. In an emergency, an email and a Short Message Service (SMS) Text are used for sending brief messages electronically, which are prompted by Global System for Mobile Communications (GSM) Standard for cellular communication networks to the receiving device. The prominent attribute of the work is the printed stretchable metal-interconnects circuit board that benefitted others in terms of budget and feasibility. Different from [45], this work underlines the importance of the orientation of the 3-axis accelerometer placement on the subject.

IoT with multi-sensor fusion in [93] carry out scalability test of system architecture for computing and storage resources relative to the growing number of monitored user. Several machine learning validations were also performed in their work and tested the detection of falls inside a Cloud-based data centre and on an Edge IoT device. The device-to-cloud data transmission confirmed that a significant size reduction of stored and transmitted data could be achieved while performing fall detection on the Edge.

In another multi-sensor fusion utilising IoT, in [94] sensor is embedded in the eyeglasses, thus addressing the point of detection on the head area. Threshold algorithm with complementary filter as a method of fall detection, Wi-Fi network is utilised for sending messages tan o emergency contact when fall occurrence is detected. Exploiting readily available sensor devices, work in [90] explore the device performance with different data acquisition scenarios, proposing comprehensive sensing (CS) for data and running several machine learning algorithms for best outcome identification.

The system in [83] consists of several microcontrollers interfacing with specific sensors. The temperature sensor is connected to Arduino pro mini microcontroller, transferring the data via an integrated Wi-Fi module to a cloud server (ThingSpeak) for monitoring. In contrast, ECG sensor data, blood pressure, and oxygen saturation level are measured using Photoplethysmogram (PPG) which is optical measurement of blood volume changes to assess heart rate and other parameters signal probe and transferred via Bluetooth to integrated development environment (IDE) software, (LabVIEW). Fall detection through acceleration data reading will only trigger the GSM and GPS module to send an alert and the subject's location to authorities upon exceeding the threshold value.

Work by [88] came out with special measures for detecting the possible fall by analyzing the unusual human gait change that can indicate a forthcoming fall. The methods proposed six force sensors installed in the shoe linings, three on each shoe. The proposed method and equipment setup is universal and adjustable according to the individual case. The accuracy of abnormality gait detection reached up to 94%. While in [87] proposing head-mounted device fall detection. The detection method was applied on the threshold with several pre-processing for each input reading and Madgwick's filter to improve the accuracy of the estimation of orientation, which is inflexible in new input data detection. The sampling frequency for the subject's posture reading is every 50 milliseconds. When the reading exceeds the threshold limit, the system will only prompt the Wi-Fi module when a fall is detected to notify the emergency contact of the user's condition. Work in [85] focuses on the feasibility of applicating smartwatches to fall detection. The choice of sensor location is due to wide acceptance, ergonomic value, and low cost of the device.

3) FALL DETECTION: AMBIENT/ ENVIRONMENT-BASED

The camera-based approach is common in fall detection systems in the ambient-based method. As in [101], the work initiates data augmentation to reduce the time spent collecting enough data and overcome the overfitting issue. Moreover, with a high-end detection algorithm, the system achieves excellent results. A significant contribution by [102] exploits the phase and amplitude of the fine-grained Channel State Information (CSI) accessible in commodity Wi-Fi devices for activity segmentation and fall detection. Further, control characteristics of falls in the time and frequency domain for accurate fall segmentation/detection and find the fall's sharp power profile decline pattern in the time-frequency domain.

The system consistently outperforms state-of-the-art fall detector WiFall [103]. Another work deploying commodity W-Fi framework is [91] by collecting disturbance signs induced by human motions and applying the discrete wavelet

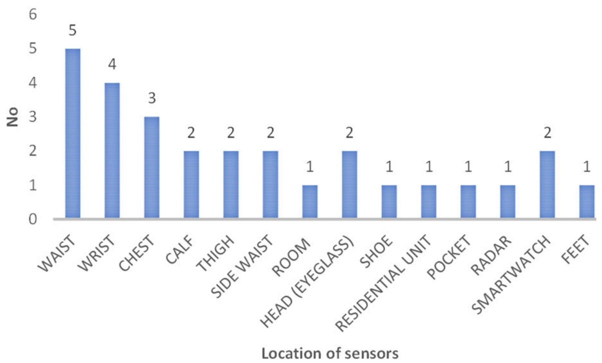


FIGURE 12. Location of sensor.

transform (DWT) method to eliminate random noise in the data. Next, a deep learning model is utilized, and data are uploaded to the proxy server from which the client application obtains the corresponding fall information.

Force sensor acts less precisely in differentiating between lying on the floor and falling; nevertheless, an accelerometer makes a good high-jolt detector an additional source for fall detection. Instead of attaching the sensor to the user, work in [97] install sensors under floor tiles and analyze both sensors' data reading for fall detection. Meanwhile, [104] captures the intricate properties of the radar returns and demonstrates profound learning detection superiority over conventional and Principal Component Analysis (PCA) which is statistical technique for data dimensionality reduction and pattern recognition based methods. A unique approach by [86] extracts Doppler signatures from Doppler spectrum signal measurement to identify falling events. The work analyses classification performance relating to the antenna orientation, polarisation effects, and radiation pattern. They also address mitigating limitations in a fall detection system based on a single sensor by considering the impact of antenna orientation in the signal model.

Most fall detection examples above use accelerometers except for the ambient-based method, which utilised cameras, radio frequency or sensors attached to the surrounding, each with advantages and disadvantages. More importantly, the purpose is for the patient / elderly to get timely assistance. The sensor's location for fall detection can be summarized in Fig 12.

III. DATA COLLECTION

Raw data from the sensors usually need an easily readable interface. As in several articles, the detection of all sensors have been interface with Arduino [19], [21], [33], [34], [42]. Generally, the Arduino (Fig 13) has a Wi-Fi connection using the external module and the specification of Ardunio is in Table 3. Alternatively, an ESP32 is also used as the interface to read the data. ESP32 microcontroller (Fig 14) has integrated Wi-Fi and dual-mode Bluetooth, a wireless communication technology that combines both Classic Bluetooth and Bluetooth Low Energy (BLE) which is Wireless communication technology for short-range connections into a single device [22]. Besides, the ESP32 has more memory capacity than the Arduino itself [19]. The ESP 32 specification is shown in Table 4. Another article used a PIC microcontroller (Fig 15) in their research to provide continuous health monitoring focusing on temperature and heartbeat. PIC microcontroller offers high performance and low power consumption [63]. The PIC microcontroller specification is shown in Table 5.

TABLE 3. Arduino specification.

Microcontroller	ATmega328
Operating Voltage	5V
Input Voltage (recommended)	7-12V
Input Voltage (limits)	6-20V
Digital I/O Pins	14 (of which 6 provide PWM output)
Analog Input Pins	6
DC Current per I/O Pin	40 mA
DC Current for 3.3V Pin	50 mA
Flash Memory	32 KB, of which the bootloader uses 0.5 KB
SRAM	2 KB
EEPROM	1 KB
Clock Speed	16 Hz

TABLE 4. Esp 32 specification.

Microcontroller	ESP32
Operating Voltage	2.2V to 3.6V
GPIO	36 ports
ADC	14 ports
DAC	2 ports
Flash Memory	16 Mbyte
SRAM	250 Kbyte
Clock Speed	Up to 240 MHz
Wi-Fi	2.4 GHz
Sleep Current	2.5 µA

TABLE 5. Pic microcontroller specification.

Microcontroller	PIC 16F887
CPU Architecture	8-bit PIC
Operating Voltage	2V to 5.5V
GPIO	36 I/O pins
ADC	14 channels
EEPROM	256 bytes
Flash Memory	14 Kbyte
SRAM	368 bytes
Internal Oscillator	8MHz
External Oscillator	20MHz

There are many differences between Arduino, Wi-Fi and Bluetooth Module (ESP32) and Peripheral Interface Controller (PIC) microcontrollers.One thing to consider in choosing the best interfacing module is probably in terms of cost. ESP 32 and PIC microcontrollers are cheaper compared to an Arduino. In terms of simplicity, Arduino is more user-friendly because it comes with open-source hardware, and the programming environment is straightforward, even for the beginner. In terms of features, ESP32 has an advantage

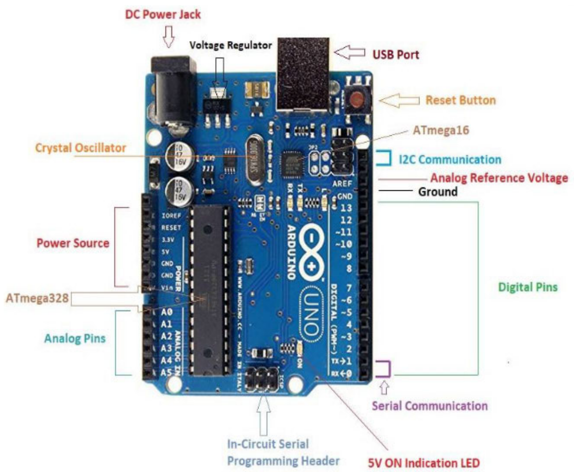


FIGURE 13. Arduino and Its specification [105].

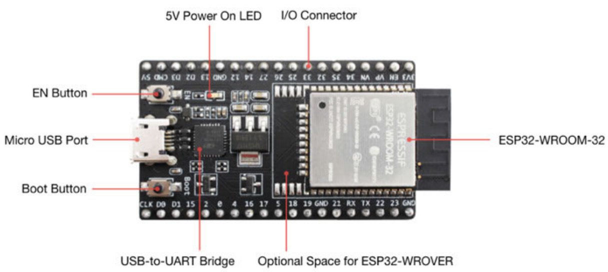


FIGURE 14. ESP 32 AND ITS SPECIFICATION [106].

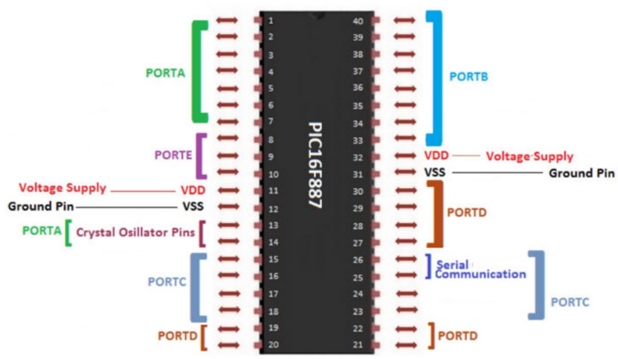


FIGURE 15. PIC microcontroller and Its specification [107].

when it already has built-in an integrated Wi-Fi and Bluetooth module. Compared to Arduino, it requires an external module to connect to wireless communication.

IV. COMMUNICATIONS

In a wireless health monitoring system, the wireless communication modules are vital to receive or send adequate data to the intended location. Wireless health monitoring systems have been developed utilizing a variety of communication technologies. It has evolved rapidly from various communication modes to fulfil the target application's requirements. Essentially, there are two main types of wireless communication, namely short-range wireless communication and long-range wireless communication. The former is usually used to communicate amongst devices within the WBAN, whilst the latter establishes a connection between the WBAN's central node and a base station or a satellite so that the data can be forwarded to the healthcare system. In this section, we will also discuss the communication protocols at the application layer which often hold substantial importance due to their critical role in addressing the unique challenges of IoT particularly for wireless health monitoring.

TABLE 6. Comparison of short-range communication technologies.

Types	Range	Data rate	Power Usage	References
Bluetooth	Bluetooth 4 10m Bluetooth 5 40m	Bluetooth 4 1 Mbit/s; Bluetooth 5 2 Mbit/s;	Bluetooth 4 Low Bluetooth 5 Very low	[42], [47], [64], [67], [69], [85], [34], [108]–[116]
ZigBee	100m	250 kbps	Very low	[19], [23], [24], [39], [63], [66], [67], [70], [117]–[122]
Wi-Fi	100m	802.11a – 54 Mbit/s; 802.11b – 11 Mbit/s; 802.11ac – 1 Gbit/s	Low-High	[21], [22], [25], [33], [36], [37], [65], [67], [70], [83], [85]–[88], [123]–[132]
NFC	20cm	424 Kbit/s	Very low	[21], [133]–[143]

A. SHORT-RANGE WIRELESS COMMUNICATIONS

Short-range wireless communication often refers to wireless communication with a range of less than a hundred meters. Short-range wireless communication is frequently employed between wireless health monitoring system nodes, most notably between sensor nodes and the central node that does data processing. While short-range communication standards can be utilized for other purposes, this survey is focused on developing a small WBAN with only a few sensors and single or multiple central nodes (i.e. MCUs) and in cases where a Local Area Network (LAN) is a network of interconnected devices within a limited geographical area to connect the central node/MCU to an access point. There are numerous short-range communication technologies, but the most frequently used health monitoring are Bluetooth, Wi-fi, ZigBee, and Near Field Communication (NFC) Short-range wireless technology for contactless data exchange. A comparison of significant short-range communication technologies is shown in Table 6, together with the list of references that employ the associated communication technologies.

Bluetooth is one of the most widely used communications technologies for personal area networks since it provides reasonably high bandwidth and is commonly implemented in commercial devices like smartphones or laptops. Bluetooth 4.0 communication provides data within the transmission range of up to 10 meters and a data rate of up to 1 Mbit/s.

In [3], [42], and [64], a low-energy version of Bluetooth 4.0, which is known as Bluetooth low energy (BLE), is employed in their health monitoring systems. BLE is advantageous in terms of its low power consumption. In 2016, Bluetooth 5 was released, enabling BLE to twice its speed (2 Mbit/s) at the expense of range or to double its capacity up to fourfold at the data rate cost [144]. The increase in transmissions may be critical for IoT devices, which connect several nodes throughout a particular area. In general, Bluetooth is an excellent fit for healthcare applications. It is secure and has a good range for WBANs, low latency, low power consumption, and robustness to interference [145]. Bluetooth has been frequently used in wireless healthcare monitoring systems enabling patients to transmit vital signals such as ECG, blood pressure, and oxygen saturation levels to healthcare practitioners [143].

Besides focuses, ZigBee is an open global standard for wireless technology that enables low-power and low-bandwidth transmissions suitable for remote monitoring, control, and sensor network applications [146]. Besides Bluetooth, ZigBee is another widely used wireless technology in WBANs since it focuses on applications that demand a low data rate and long battery life. A ZigBee network is much easier to manage and less expensive than another wireless personal area network [24]. Additionally, ZigBee networks have a low transmission delay, making them ideal for medical system requirements [23], [66], [122]. ZigBee is expected to play a significant role in wireless healthcare monitoring systems by transmitting physical parameters between patients and healthcare providers. The primary disadvantage of ZigBee is that key exchange can be compromised unless the manufacturer implements it extremely well [145]. Additionally, ZigBee is not frequently used in mobile devices such as smartphones, whereas BLE is. As a result of this, it is suggested that ZigBee would be better suited to fixed-location, standalone applications such as home automation than wearable healthcare systems [145].

Another popular mode of communication is the Wi-Fi connection. Wi-Fi includes the IEEE 802.11a/b/g/ac standards for wireless local area networks. Connecting to an access point (AP) or operating in ad hoc mode enables users to surf the Internet at broadband speeds. Additionally, Wi-Fi gives the high-speed connectivity of Ethernet without the need for a connection. When near an AP, a person can connect to the Internet using a Wi-Fi-enabled device such as a computer, smartphone, or handheld device. Nowadays, Wi-Fi has played an essential role in modern society due to its unique properties, such as extended transmission distance, rapid transmission speed, interoperability with other services, and security. In telemedicine devices, Wi-Fi has been employed to send data to the intended location [33], [36], [37], [87], [88]. As mentioned in [22], using a microcontroller equipped with a built-in Wi-Fi module simplifies collecting data and wirelessly transmitting it to IoT websites.

Near-field communication (NFC) technology enables non-contact point-to-point data exchange between electronic devices within a range of about 20 cm [145], [147]. This technology is based on RFID and connectivity technologies investigated and developed by Philips, Nokia, and Sony. NFC operates at a frequency of 13.56 MHz and transmits data at a rate of up to 424 Kbit/s. NFC technology has gained widespread popularity among mobile phone vendors and related fields owing to its compatibility with already-established technologies such as RFID, smart cards, and contactless cards. NFC applications in telemedicine monitoring have recently received increased attention [142], [143]. It is anticipated that the rapid advancement of information technology will inevitably influence the healthcare system soon.

TABLE 7. Comparison of long-range communication technologies.

Types	Range	Data rate	Power Usage	References
Sigfox	50Km	300 bit/s	Low	[145], [148], [149]
LoRaWAN	45Km	50 kbit/s	Low	[150]–[155]
NB-IoT	35Km	250 kbit/s	Medium	[156]–[162]
Cellular technologies (GSM, GPRS)	35Km	GSM – 9.6 kbit/s; GPRS – 115.2 kbit/s	High	GSM [20], [23], [45], [63], [65], [71], [83], [108], [163], [164] GPRS [84], [165], [164]
Cellular technologies (4G, 5G)	10Km	4G – 12 Mbit/s; 5G – 3.6 Gbit/s	High	4G [167]–[170] 5G [149], [171]–[178]
EC-GSM	100Km	140 kbit/s	Medium	[145], [179]
LTE-M (M1)	11Km	1 Mbit/s	Medium	[145], [179], [180]
Satellite (GPS)	>20,000Km	50 bit/s	High	[45], [83], [85], [181]–[185]

B. LONG-RANGE WIRELESS COMMUNICATIONS

Short-range wireless communication provides communication between the sensors and devices within the WBAN. The information from the sensors or MCUs was not meant to be kept and needs to be forwarded to the hospital/medical information system or the doctor in charge, which may be located hundreds of miles away from the patients. This can be accomplished using long-range backhaul communications through a wide-area network (WAN). A comparison of significant long-range communication technologies is shown in Table 7, together with the list of references that employ the associated communication technologies.

In smart healthcare, various wireless communication technologies can be used to transfer data over a long distance between a central node to a base station/satellite. Low-Power Wide-Area Networks (LPWANs) are a subset of long-range communication standards that are well-suited for IoT applications. An LPWAN typically has a range of several kilometres, even in an urban environment. This is significantly longer than the range of traditional IoT communications technologies such as Wi-Fi or Bluetooth. LPWANs are suitable for a variety of healthcare applications, including general and critical health monitoring, receiving emergency calls, and rehabilitation. Additionally, this design principle enables low-power device design, extending the time between human involvement to recharge or swap batteries. Among the most prominent standards for LPWANs are Sigfox, long-range radio WAN (LoRaWAN), and narrowband IoT (NB-IoT).

Sigfox is an ultra-tight band radio technology with a comprehensive star-based framework that creates a highly adaptable worldwide network for innovative healthcare applications with extremely low power consumption [148]. In urban areas, Sigfox has a maximum range of 9.5 kilometres with a low data rate of 100b/s, while in rural areas, Sigfox has a range of up to 50 kilometres with a data rate of 300b/s. Sigfox is well suited for non-critical applications in which message delivery speed and reception acknowledgements are not vital. However, in healthcare, it is critical to transfer messages at a reasonable rate successfully. Any security breach could harm an individual's health or the integrity of medical databases. As a result, it is recommended in [145] that Sigfox not be used in mission-critical healthcare applications.

LoRaWAN is a network layer protocol built on top of the LoRa specification [186]. It has a star architecture, and nodes connect only when necessary, such as after an event or scheduled measurement. Additionally, LoRaWAN has a high network capacity, which enables the transmission of many messages simultaneously over the network. Due to its range, latency, and network capacity, LoRaWAN is generally well-suited for healthcare applications. Similar to Sigfox, LoRaWAN works in unlicensed bands, so security and interference may be a concern.

NB-IoT, which was just standardized in 3GPP Release 13, works in permitting the global system for mobile communications (GSM) or long-term evolution (LTE) channels and enables long-range, low-power communications [162]. Because NB-IoT is based on LTE, most of the existing LTE hardware may be utilized to deploy it quickly and effectively. The primary advantage of operating inside licensed bands is the lower chance of interference. However, one potential downside is that NB-IoT costs will almost certainly be higher than unlicensed bands. NB-IoT has a range of up to 35 kilometres due to its high receiver sensitivity of 164 dB and can achieve the highest uplink data rate of 250 kbit/s [145]. The high data rate and extensive range make it excellent for healthcare applications, as messages can reach a reasonable distance quickly for even the most crucial health situations. NB-IoT is well-suited for medical applications. It is secure, allows long-range communications, is energy efficient, and can accommodate many devices. The primary disadvantages are the current lack of deployment and higher power usage compared to other Low-Power Wide-Area Networks (LPWANS) which are wireless networks designed for long-range communication with low power consumption such as Sigfox and LoRaWAN.

Another mode of long-range communication is cellular communication technologies, for example, GSM, GPRS, 3G Universal Mobile Telecommunications System (UMTS), 4G LTE which is standard for high-speed wireless communication for mobile devices, and 5G LTE-Advanced. Cellular communication technologies, particularly 4G and 5G, can deliver extremely high data rates with ultra-low latency, making them ideal for critical healthcare applications that require real-time multimedia content transfer [149]. Furthermore, the cellular network is widely deployed in most places. However, because cellular communication technologies are designed for mobile phone applications, they have a significant power consumption and are, therefore, unsuitable for IoT applications. Extended Coverage—GSM (EC-GSM) was introduced to improve GSM for IoT usage, exploiting the existing GSM network. Enabling EC-GSM requires updating the software on current GSM gateways. EC-GSM improves coverage by up to 20 dB, supports up to 50,000 devices per gateway, and offers a data rate of less than 140 kbit/s for both uplink and downlink, which is slower than NB-IoT [187]. The power-saving version of LTE for IoT applications, known as the LTE Machine Type Communications Category M1 (LTE-M), also has been developed to utilize the capacity of an LTE carrier while improving the battery life of IoT devices and expanding the coverage of the network. LTE-M, with a maximum data rate of 1 Mbit/s, enables more advanced IoT applications. However, it has a limited range and can accommodate only about 20,000 nodes per gateway [145]. LTE-M is unquestionably an ideal solution for a system that requires fast speed, enormous amounts of data, and advanced functionality. This may not be the case for many healthcare applications that transmit small amounts of essential data intermittently and would benefit from long-range, high-capacity gateways, such as those found in NB-IoT [145].

The satellite is one of the communication systems that provide global coverage. Satellite communications enable the provision of various wireless services, including the GPS. Generally, GPS has been used to determine position and timing and to direct the user to a specific location. In this scenario, some researchers have used GPS to determine the user's location for fall detection applications [45], [83], [85].

C. COMMUNICATION PROTOCOLS

Data exchange is crucial in IoT, and the application layer provides the messaging functionality needed to make IoT services work. The choice of the application layer communication protocol plays a pivotal role in determining the efficiency, reliability, and real-time responsiveness of wireless healthcare monitoring systems. By selecting the most suitable protocol based on the specific requirements of the application, healthcare providers can ensure seamless data exchange, timely interventions, and improved patient outcomes. Among the key application layer communication protocols that cater to different aspects of healthcare monitoring are Message Queuing Telemetry Transport (MQTT), Constrained Application Protocol (CoAP), Extensible Messaging and Presence Protocol (XMPP), and Advanced Message Queuing Protocol (AMQP).

MQTT is a messaging transport protocol that is based on publish-subscribe architecture and it was first introduced in 1999 [188]. MQTT has gained prominence as a robust and efficient communication protocol within wireless healthcare monitoring applications [189], [190], [191]. Operating on the publish-subscribe model, MQTT enables medical devices to publish health data to specific topics, which are then subscribed to by authorized healthcare providers or monitoring systems. This real-time data exchange mechanism proves invaluable in scenarios requiring prompt medical interventions or remote patient care. MQTT's lightweight nature ensures minimal overhead on devices, making it well-suited for resource-constrained wearable devices and sensors.

Considering that many IoT devices possess constrained power and storage capabilities, the CoAP protocol serves to extend the functionalities of the Hypertext Transfer Protocol (HTTP), which tends to be relatively complex, by catering to the specific requirements of IoT devices [192]. CoAP'sl architecture makes it ideal for interfacing with web services, allowing healthcare data to be easily integrated into existing medical systems. CoAP's design aligns with the requirements of wearable health trackers and remote patient monitoring, where energy efficiency is crucial [193]. With its low overhead and efficient message serialization, CoAP ensures effective communication over wireless links with minimal energy consumption.

In wireless healthcare monitoring, real-time communication and presence tracking are often essential. XMPP, originally designed for instant messaging, has been adapted for healthcare applications to provide timely alerts and seamless communication between patients, caregivers, and medical professionals [194], [195]. XMPP's support for presence management aids in tracking patients' status, making it suitable for emergency scenarios and timely interventions.

AMQP is an open standard designed for facilitating business communication between applications, functioning asynchronously across diverse entities and platforms to provide message services such as privacy, queuing, durability, and routing [196], [197]. It operates as a wire-level protocol, enabling the reliable exchange of business messages. AMQP's focus on reliable message queuing finds applicability in healthcare monitoring systems that demand stringent data integrity and guaranteed delivery [198]. Its sophisticated message broker architecture ensures that health data is transmitted and processed reliably, making it suitable for critical healthcare applications that involve data analysis and processing pipelines.

V. CONCLUSION

A total of thirty-five papers have been selected for review. The summarization of the research findings has been noted in Table 1 above. Based on Fig 2, it can be said that most of the papers reviewed focus on measuring the heart rate followed by measuring the body temperature. The table shows that the sensor used for measuring the heart rate mainly uses a piezoelectric sensor or MAX30100, a type of built-in pulse oximetry (for measuring blood oxygen) and a heart rate sensor. A typical sensor for body temperature, which is LM35, has been selected by most researchers due to its suitability and ease of setup. However, as this type of sensor is used for measuring body temperature, it needs to be attached to the skin compared to other sensing materials. The usual device will be equipped with a pressure sensor and a cuff to measure blood pressure. This type of measurement is more accurate compared to the available market smartwatch. The same goes for ECG measurement. ECG measurement is also available in a variety of smartwatches. However, in case of accuracy, the user needs to consult the doctor for further examination.

For the fall detection sensor, 18 papers have been reviewed, as shown in Table 2, where the most common sensor used is the accelerometer sensor. By referring to the table, waist and wrist are the selected places to wear for the fall detection sensor. Theoretically, when comparing the wrist and the waist, it is better to put the sensor at the waist because the wrist will make a lot of movement compared to the waist position. Furthermore, fall detection usually happens instantly, requiring instant feedback. Based on the review, most of the features of the fall detection sensor will make it end up sending an alert message to any emergency contact.

Furthermore, the communication part must be appropriately determined to make a system work wirelessly. Many types of communication can be used to transfer the data to the receiver. Usually, in a perfect system, various kinds of communication have been used, for example, GPS to track location and Wi-Fi to transmit the data to the cloud.

Many existing healthcare monitoring systems rely on Wi-Fi for short-range communication due to its availability and ease of use/setup. Wi-Fi can provide a high data rate but at the expense of significant power consumption. Due to this, Wi-Fi is typically utilized to connect the central node/MCU to the AP and is not ideal for WBAN. Meanwhile, Bluetooth or BLE is an excellent fit for healthcare applications, especially to provide communication links for WBANs. It is secure and has a good range for WBANs, low latency and low power consumption.

Meanwhile, ZigBee is also a good alternative for short-range communication, particularly for WBANs, as the ZigBee network is much easier to manage and less expensive than other wireless personal area networks. However, ZigBee is not frequently used in mobile devices such as smartphones, whereas BLE is. As a result, it is suggested that ZigBee would be better suited to fixed-location, standalone applications than wearable healthcare systems.

Many systems rely on GSM messaging services for long-range communications to offer simple updates from sensor readings and to transmit an alert message over a long distance. However, GSM's power consumption is high and unsuitable for IoT applications. Meanwhile, an LPWAN is a subset of wireless technologies well-suited to the unique requirements of machine-to-machine and IoT devices. The long-range and low-power design features of LPWANs are suitable for various healthcare applications, including general and critical health monitoring, emergency calls, and rehabilitation. Among the most prominent standards for LPWANs are Sigfox, LoRaWAN, and NB-IoT. Sigfox and LoRaWAN work in unlicensed bands, so security and interference may be a concern as opposed to NB-IoT, which operates in licensed bands. However, NB-IoT is more expensive and consumes more power than Sigfox and LoRaWAN. Cellular communication technologies, notably 4G and 5G, can deliver extremely high data rates with extremely low latency, making them perfect for mission-critical healthcare applications requiring real-time multi-media content transfer. The main drawback of cellular communication technologies is the high-power consumption as they were developed for mobile phone applications. Alternative technologies have been developed for IoT applications based on cellular communication technologies such as EC-GSM and LTE-M providing a more extended range and lower power consumption than conventional cellular technologies. Besides, the satellite service GPS also has been used to determine users' location, especially for fall detection applications. Each mode of communication has several benefits and drawbacks. The type of communication to be used must be appropriately selected and meet the system's specifications.

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