Mobile and Wearable Sensors for Data-driven Health Monitoring System: State-of-the-Art and Future Prospect

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Title Page

Mobile and Wearable Sensors for Data-driven Health Monitoring System: State-of-the-Art and Future Prospect

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Mobile and Wearable Sensors for Data-driven Health Monitoring System: State-of-the-Arts and Future Prospects

Abstract

Mobile and wearable devices embedded with multiple sensors for health monitoring and disease diagnosis are growing fields with the potential to provide efficient means for remote health management. A sensor-based health monitoring system offers an essential mechanism for real-time diagnosis and management to detect/predict, recommend treatment and prevent the onset of diseases. This paper aims to synthesize the research efforts on mobile and wearable sensors for health monitoring. It will investigate sensors, components of health monitoring systems, major application areas, challenges, and solutions faced during the implementation of health monitoring systems by researchers and practitioners. It was observed that sensors embedded in mobile and wearable devices for health monitoring are broadly categorized into homogeneous, dual, and heterogeneous sensors. In health monitoring, heterogeneous sensor-based is widely implemented and the most effective due to its ability to combine multiple sensors from various domains. The fusion of multiple sensors provides reliability, credibility, and better accuracy for monitoring multiple health parameters. We observed that researchers follow established procedures such as data collection, data transmission, preprocessing, feature extraction and development, data analysis, and evaluation of different algorithms for implementation of the health monitoring system. Supervised machine learning algorithms such as support vector machine, decision tree, k-nearest neighbors, and deep learning methods were the most implemented methods, while accuracy was the favored evaluation measure for health monitoring. Generally, we found that a health monitoring system is implemented to resolve health issues in the areas of human activity and posture monitoring, sleep disorder, sleep stage detection, fall monitoring in the elderly, depression, and mood swing detection. Other important areas include Parkinson's disease management, cardiac diseases monitoring, disease diagnosis, and well-being, and Corona virus detection and contact tracing to minimize infection rate. Furthermore, the review succinctly highlights various challenges impeding the development of sensor-based health monitoring systems with significant solutions that were recommended in the literature to ameliorate these challenges discussed. From the review, it can be acknowledged that various research efforts have been conducted to develop effective health monitoring systems, and many new systems have been implemented. However, there is still much work to be done which we have also discussed under future prospects.

Keywords: Machine Learning, Mobile and Wearable Sensors, Health monitoring, Disease Management, Internet of things, Coronavirus, Review

1. Introduction

In recent times, various computing devices are emerging to proffer solutions and ensure efficiency in healthcare and telemedicine. Information technology and telemedicine devices have brought significant changes needed in the healthcare environments especially with the fusion of technologies that provided miniaturized devices and improvement in areas of data transmission speed, affordability, convergence, portability, personalization, collaboration, and cloud storage. The digital-driven technology such as mobile phones, wearable sensors, and internet of things (IoT), internet of medical things (IoMT), and internet of everything (IoE) (Masoud, Jaradat, Manasrah, & Jannoud, 2019) is conveniently deployed in the healthcare system to achieve high thorough-put in human health monitoring.

Therefore, wearable and mobile based-sensors are an integral part of the new telemedicine concept supporting the idea that information will improve the quality and efficiency of the healthcare system (Breitegger, 2018). Hence, wearable computing is a phenomenon that generally refers to miniaturized electronic technologies that can be incorporated into items of clothing and accessories, and comfortably worn on the body (Amft, 2018).

Wearable computing facilitates a new form of interaction between the human and the computer comprising a small body-worn computer that is always accessible and ready for use. For instance, the use of a shoe, embedded with inertial sensors, will enable the detection of sidewalk-to-street transitions, thereby enabling people to identify the pedestrian risks when they step into the street pavement (Shrestha and Saxena, 2017). Moreover, with mobile and wearable devices, health practitioners can observe changes occurring from time to time in the human body, and utilize these information changes to improve the wellbeing of an individual (Swaroop, Chandu, Gorrepotu, & Deb, 2019). Consequently, the essence of the health monitoring system is to provide patients, health personnel, and healthcare provider with services for maintaining healthy populations. These services include abilities to offer feedback messages into a system that reviews the current control methods in place, ease of access to patient data, and deliver higher-quality care to more patients with a lower risk of burnout. In addition, a health monitoring system ensures lower costs healthcare services provision and higher efficiency for the overall wellbeing of an individual. With wearable and mobile devices, patients can independently maintain healthy lifestyle, prevent complications and minimize personal costs. Furthermore, health monitoring systems will enable data management of patients and healthcare providers efficiently.

Besides, the integration of mobile-based applications and wearable sensors for health monitoring, the system has been widely utilized in different areas of human health monitoring. These areas include Coronavirus disease contact tracing and testing (Alo, Nkwo, Nweke, Achi, & Okemiri, 2022; Bashir, Hamid, Zahoor, & Amin, 2020) human activities identification (Michelsen et al., 2020), fall detection (Lee, Yeh, Kim, & Choi, 2018), cardiovascular diseases (Badar, Haris, & Fatima, 2020), and motion state and stress detection (Zhou, Lu, & Hu, 2020). Others include depression and mood swings (Jaworska, Salle, Ibrahim, & Blier, 2019), cardiac disease management (Etiwy et al., 2019), disease diagnosis and wellbeing (Nedungadi, Jayakumar, & Raman, 2018), and posture monitoring (Acharya, Gandhi, Karkera, Ghagare, & Deshmukh, 2019). In addition, mobile-based applications provide a platform to combine different analysis and visualization means which is highly needed in human healthcare monitoring due to their nature of interpretation.

In mobile-based application implementation and interpretation, machine learning algorithms such as support vector machine (SVM), decision-tree, K-means, Naive Bayes, neural network, and random forest play vital roles in combining and analysing the extracted data from sensor data to predict optimum healthcare status.

Presently, the existing system has some peculiar problems that inhibit effective health monitoring systems in our daily activities. Various authors pinpointed some inherent challenges facing healthcare service delivery among the users. For example, a recent study by (Subasi, Bandic, & Qaisar, 2020) highlighted the problem of conventionally scheduling an appointment with doctors for physical examination. Also, elderly people are not properly monitored as a result of a lack of an automated platform to communicate with doctors and healthcare providers remotely (Al-khafajiy et al., 2019). Consequently, the major problem of mobile and wearable sensors-based monitoring focuses on the high cost of devices for human health monitoring, delay in diagnosis, testing, and analysis of diseases and mental health disorders, inaccurate report generation and diagnosis analysis, and inability to secure patient information (Cornet & Holden, 2017).

A good number of research studies have been carried out on health monitoring systems, in recent times. Some of these studies have reviewed the sensor and mobile-based technologies for the healthcare system. For instance, the earlier review by Habib et al., (2014) presented a survey of smartphone-based approaches for fall detection and prevention. People, especially the elderly that have a history of neurodegenerative diseases suffer from these health-related issues. However, the review focuses on fall detection and prevention using a smartphone. Essential health monitoring system components such as architecture, application areas, and general challenges and solutions were not discussed. Also, Cornet and Holden, (2017) review smartphone-based passive sensing for general wellbeing to address the biomedical informatics literature. However, the systematic review only focuses on passive sensing data using smartphones on individuals that have a medical history such as bipolar disorder, schizophrenia, depression, aged people, and the general population for general wellbeing. A more recent study by Heikenfeld, Rogers, Pan, Khine, & Wang, (2018) review wearable technologies that can extract data from the body system without any form of sensor implant. The sensor modalities such as mechanical, electrical, optical, and chemical sensors were discussed. Nonetheless, the review doesn't extend to mobile phones with sensor integration and other technology such as IoT, IoE, and IoMT for health monitoring. Furthermore, the study failed to highlight system architecture for human health monitoring, major health monitoring domains, challenges, and solutions. A closely related study was presented by Nweke, Teh, Mujtaba, & Al-Garadi, (2019) on data fusion and multiple classifier systems approach for human activity recognition utilizing mobile and wearable sensors.

Nevertheless, the current survey differs from their study in many ways. *First*, while the review focused on motion sensors in the restricted activity recognition domain, the current study broadly categorized various sensors for health monitoring, comprehensive application domains, their strengths, and weaknesses. *Second*, we discussed components of health monitoring systems with machine learning approaches for making informed healthcare decisions. *Finally*, the review highlights various areas of health monitoring that recently implemented sensor-based approaches, and the types of data prevalent in these areas. In addition, the study outlined various challenges impeding the effective implementation of the health monitoring system, and the solutions to ameliorate these issues. Consequently, this review is a well-timed investigation of mobile and wearable devices, sensors categories, system architecture, and future prospects of health monitoring systems. From available studies in literature, there are no comprehensive reviews or surveys that provide important discussion in these all-encompassing technology-based health themes.

Accordingly, the contributions of this review to the current body of knowledge in mobile and wearable sensor-based health monitoring systems are as follows:

- To provide an in-depth explanation of mobile and wearable sensors for health monitoring systems, strengths, and weaknesses;
- To comprehensively summarize system architecture for health monitoring;
- To identify and discuss recent disease diagnosis domains of mobile and wearable sensors for health monitoring, issues, and data types;
- To provide analysis on critical challenges inhibiting sensor-based health monitoring systems, and solutions recently proposed in the literature;
- To point out current research gaps and future prospects in the implementation of sensor-based health monitoring systems.

The remainder of this paper is organized as follows: section 2 provides research methodology. Section 3 presents a review of mobile and wearable sensors for health monitoring systems, categories, strengths, and weaknesses. Section 4 highlights health monitoring system architecture which includes data collection, transmission, pre-processing, feature extraction, system modeling, and evaluation parameters. Section 5 explores key application areas of mobile health monitoring systems while a review of major challenges and solutions are highlighted in section 6. In addition, section 7 presents the discussion while open research directions are presented in section 8. Finally, Section 9 concludes the review. The taxonomy of mobile and wearable devices for health monitoring is shown in Fig. *1*.

Table 1. List of Acronyms used in the paper.

Acronym	Meaning	Acronym	Meaning
ADLs	Activities Daily Living	IoT	Internet of Things
BCI	Brain Computer Interface	IoMT	Internet of Medical Things
DMD	Depressive Mood Disorder	mHealth	Mobile Health
CAD	Coronary Heart Disease	GPS	Geographical Positioning System
COVID-19	Coronavirus 19	MDD	Depressive Major Disorder
CVD	Cardiovascular Diseases	mPDS	Mobile Parkinson Disease Score
ECG	Electrocardiography	NCDC	Nigeria Centre For Disease Control
EEG	Electroencephalography	QRS	Quasi Random Signal
EMG	Electromyography	PPG	Photoplethysomography
EMA	Ecological Momentary Assessment	PRV	Pulse Rate Variability
EBOV	Ebola Virus Disease	SCG	Seismocardiography
HR	Heart Rate	SPO_2	Pulse Oxygen Saturation
HRV	Heart Rate Variability	SHMS	Smart Healthcare Monitoring System
IoET	Internet of Everything	SW	Wearable Sensor
		ZKV	Zika Virus

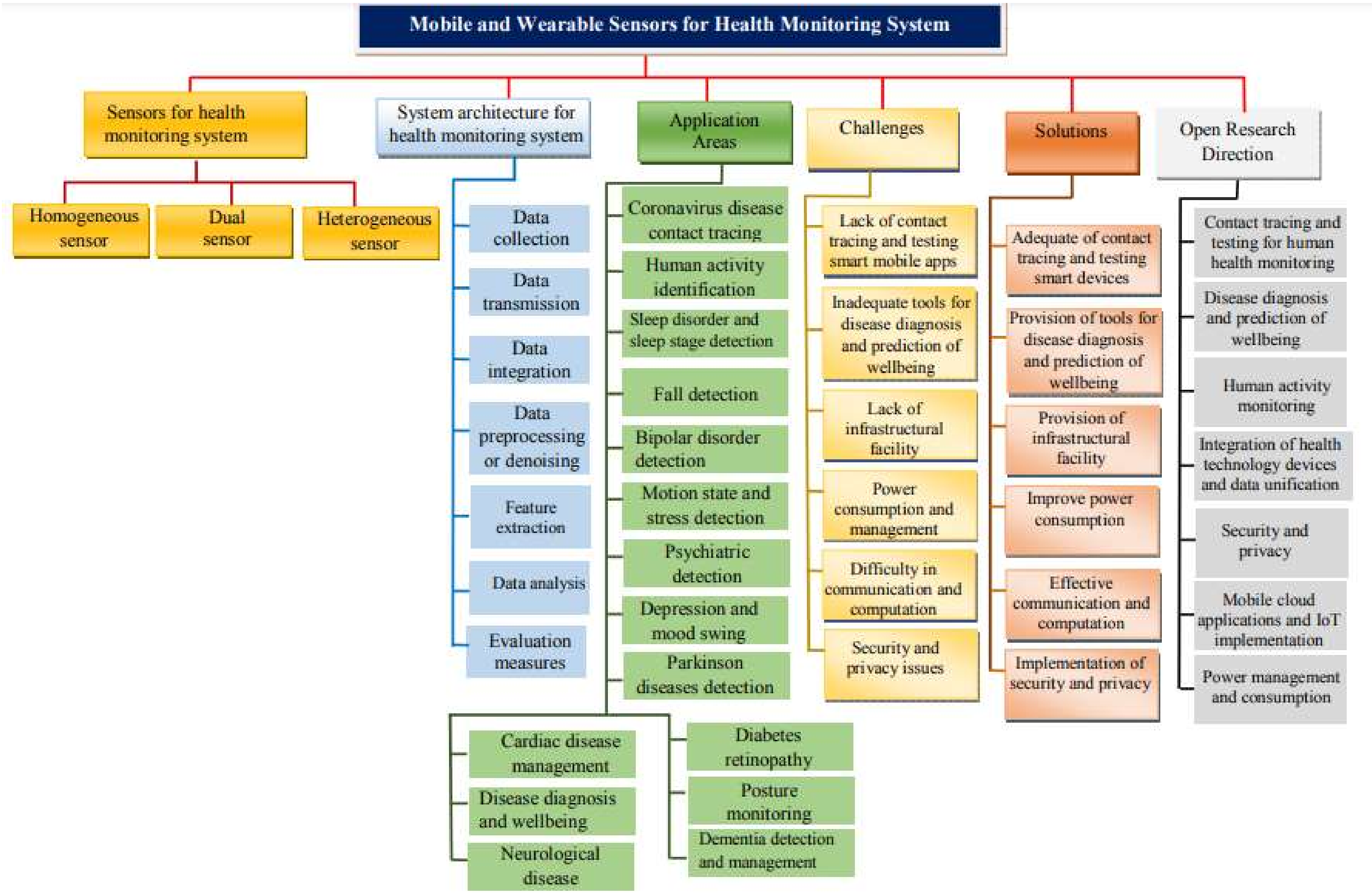

Fig. 1. Taxonomy of Mobile and wearable sensors for health monitoring system.

2. Methodology

This study provides essential information on sensor-based health monitoring, components of health monitoring systems, applications, and challenges. To ensure comprehensive coverage of recently developed methods in this area, the study adopted a systematic literature review procedure widely applied in Computer science and Engineering study (Kitchenham, 2004). The procedure adopted includes research questions identification, selection strategies, inclusion and exclusion criteria, and extraction of study characteristics. The procedure is briefly described below. In addition, Fig. 1 diagrammatically presents the primary studies analysis process.

2.1 Research Questions

Q1: What are the major sensors for effective health monitoring implementation?
Q2: What are the consistent architectural components of health monitoring systems?
Q3: How to identify the strengths and weaknesses of each sensor?
Q4: Are there effective applications of the identified sensors, attributes, and examples?
Q5: What are the challenges hindering the development and deployment of sensors for health monitoring?
Q6: How to identify solutions to address the challenges
Q7: Which future research prospect is the focus of researchers in sensor-based health monitoring?

2.2 Search strategy

The main aim of this study is to comprehensively review and outline various components of health monitoring systems. Therefore, the study performed an electronic search of various academic research databases. The databases considered in the review include ACM Digital Libraries, Web of Science, Google Scholar, IEEE Xplore, Scopus, PubMed, and Medline. All the extracted articles were independently evaluated by all the researchers (*CVA*, *HFN*, *ACI*, *CAE*, *FUO*, and *URA*) for suitability. Moreover, the studies were examined for their relevance and coverage of research objectives. This article discusses and targets human health monitoring implementation, describes sensors used, data collection procedure, and analysis. Initially, 2023 articles were retrieved from the database as explained in section 2.1.

2.3 Extraction of Characteristics

Following the research question itemized in section 2.1, we extracted the following data from the selected article: year of publication, the type of sensors used in the implementation of health monitoring systems, data collection procedure, major challenges if any, and evaluation process of the proposed health monitoring systems. Subsequent sections of the article discuss the outcome of the evaluation of each article presented in the systematic review. During the initial screen, the authors eliminated duplicate copies, studies that do not point to human health monitoring, and studies without full-text. The inclusion criteria used to select the most relevant studies include:

- The articles are original and published in journal or conference proceedings;
- The publication is within 2014 to 2021;
- The article is written in English Language and has full-text access;
- The article has sensor-based health monitoring, and well-defined system implementation architecture;
- Target specific health monitoring applications using varieties of sensors.

The exclusion criteria adopted to select the primary studies include:

- The study is not relevant to the research questions outlined in section 2.1;
- The study is not considered original such as reviews, letters, and comments to the editor.

Initially, the search strategies through the outlined databases (section 2.2) produced 2023 studies. Then, after excluding duplicate copies of the studies, 1431 records were considered for screening. Further reading of the selected article's title and abstracts decreased the number of articles to 575 which did not meet the outlined inclusion criteria. Furthermore, full-text of the studies were retrieved and reviewed by the authors for relevance, suitability, and eligibility. After excluding irrelevant studies, 85 articles were included in the final review. The primary studies selection procedure is shown in Fig. 2, and Table 2.

253

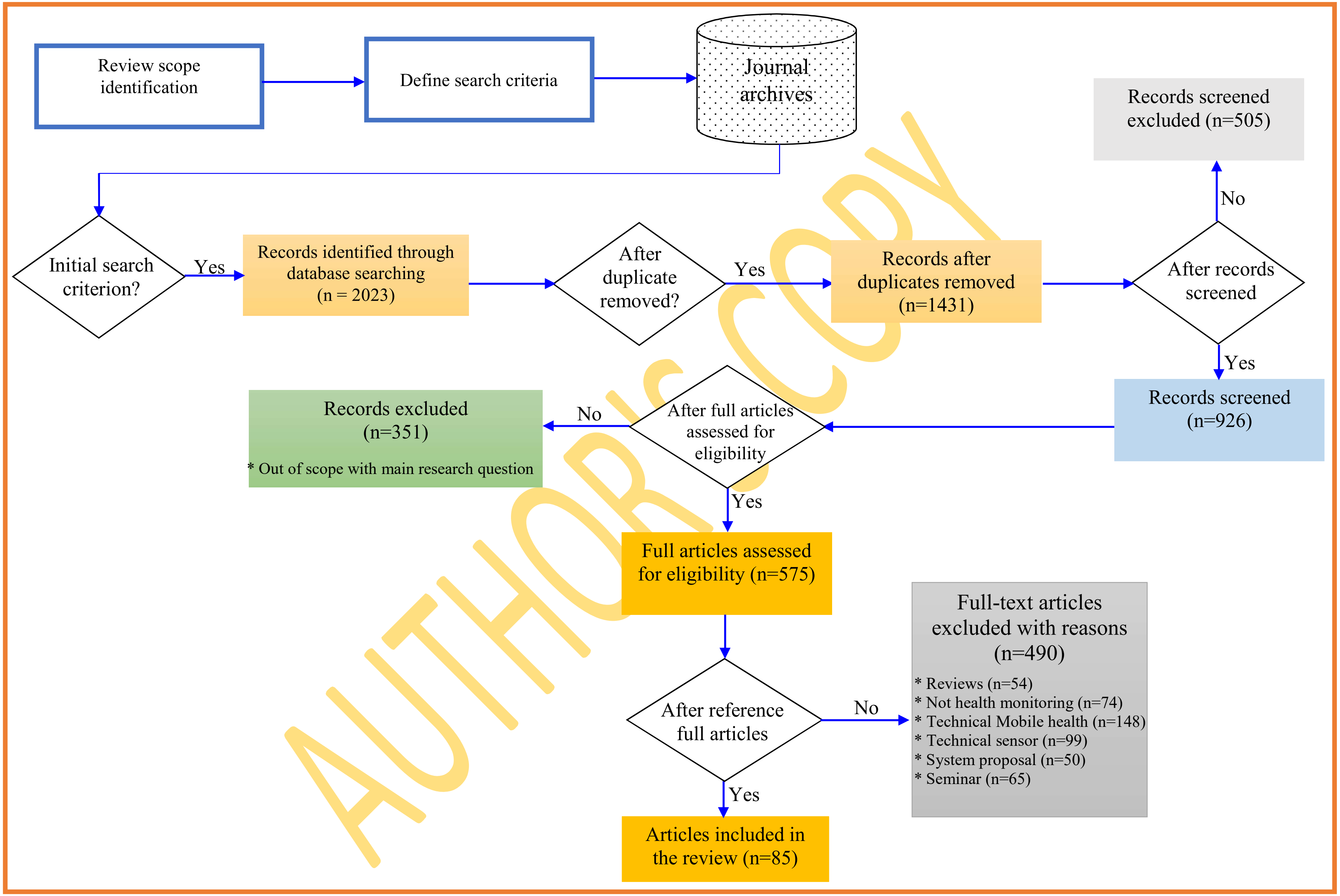

Fig. 2. The article analysis process.

Table 2. The article analysis process.

Database	Initial search	Record after duplicate removed	After abstract screening	After full-text screening	After reference scanning	After quality assessment
ACM Digital Library	241	136	106	88	11	8
IEEE Xplore	286	606	306	230	16	13
Google Scholar	317	293	193	99	20	14
Scopus	320	121	101	65	9	9
WoS	200	129	100	42	10	8
PubMed	103	31	25	8	7	7
Science Direct	227	67	47	15	11	10
DOAJ	141	20	20	11	6	5
Medline	86	13	13	7	6	6
SpringerLink	102	15	15	10	5	5
Total	**2023**	**1431**	**926**	**575**	**101**	**85**

3. Mobile and wearable Sensors for Health Monitoring System

This section discusses the sensors used for mobile and wearable devices for effective health monitoring services. Wearable sensor (Breitegger, 2018; Deshpande & Kulkarni, 2017) is a fundamental part of the new telemedicine paradigm designated to support the perception that quality and healthcare delivery services will improve through the utilisation of effective information and digital devices. The wearable sensors are the hardware component that captures different types of signals such as activity, physiological and environmental signals and are embedded in our daily devices such as smartphones, smart watches, head-worn, etc., and other wearable medical devices. In addition, the use of sensors in various areas such as human activity recognition, sleep disorder detection, fall detection, motion state, and stress detection, cardiovascular disease management, and disease diagnosis of well-being not only potentially changes medical practice but also one's relationship with one's body and mind, as well as the role and responsibilities of patients and healthcare professions. Furthermore, the use of wearable sensors has made the diagnosis, treatment, and monitoring possible at home and other remote locations for patients after an attack of diseases or other life-threatening and emerging virus infectious diseases such as Coronavirus (COVID-19) (Tao et al., 2020), Zika virus (ZKV) (Ozdener et al., 2020), Ebola virus disease (EBOV) (Jacob et al., 2020), etc. For instance, various sensors have been developed over the years for effective health monitoring and diagnosis of diseases. Some of the sensors include Electrocardiography (ECG), Accelerometer, Electroencephalography (EEG), Photoplethysmography (PPG), Geographical Positioning System (GPS), Electromyography (EMG), Gyroscopes, Pedometer, and Pulse Oximeter. These sensors have been deployed individually or in combination with others for health monitoring. In this section, we discuss these sensors under the different classifications. These include homogeneous sensors, dual sensors, and heterogeneous sensors.
The taxonomy of the mobile and wearable sensors for health monitoring systems is depicted in Fig. 3.

Fig. 3. The taxonomy of mobile and wearable sensors for health monitoring system.

As depicts Fig. 3, taxonomy of the mobile and wearable sensors deployed for health monitoring is classified into three; homogeneous (one sensor), dual (two sensors), and heterogeneous sensors (three or more sensors). This taxonomy is based on the critical review of previous studies that implemented sensor-based health monitoring system. In this regard, homogeneous sensors discuss studies that utilised single sensors to monitor various health parameters. On the other hand, dual sensors categories discussed studies that utilize two set of sensor to increase the reliability of health monitoring system. While heterogeneous sensors are classified under studies that deployed multiple sensors to track and detect multiple health parameters. From the studies reviewed and shown in Fig. 3, nine (9) studies utilised homogenous sensors for health monitoring, while nine (9) utilised dual sensors for health monitoring. Nonetheless, heterogeneous sensors were highly favoured in development of health monitoring as total of seventeen (17) studies implemented heterogeneous sensors for efficient and all-encompassing health monitoring as shown in fig. 3(c). Moreover, further details of the mobile and wearable sensors as utilised by various authors for health monitoring is contained in section 3.1, 3.2, 3.3 respectively, and summarized in Table 3.

3.1 Homogeneous Sensors

Homogeneous sensors are classified as a single sensor that is utilised by researchers for the effective implementation and deployment of health monitoring systems. In our extensive review, we identified nine (9) homogeneous sensors which include Electrocardiography (ECG), Accelerometer, Electroencephalography (EEG), Photoplethysmography (PPG), Geographical Positioning System (GPS), Electromyography (EMG), Pedometer, Pulse Oximeter, and Temperature sensor. These sensors are discussed as follows:

(a) Electrocardiography sensor

Electrocardiography (ECG) or electrocardiogram (Wannenburg, Malekian, Member, & Hancke, 2018) is a sensor that checks valuable information about the cardiovascular system by evaluating electrical heart-related activity such as heartbeat and heat waves. ECG sensor is employed to detect any cardiovascular disease or related abnormalities in heart functionality, analyse the heart's rhythm and detect irregularities. Moreover, ECG is used to detect other cardiac issues that might lead to serious health problems such as stroke or heart attack. ECG sensor is very important because it progressively acquires, amplifies, filters digitalizes, and transmits the ECG signals for effective health monitoring implementation. Several studies have utilised the ECG sensor for effective heart-related health checks and monitoring. For instance, an earlier study by Lee et al., (2014) implemented easy capacitive electrodes for motion artefacts reduction which efficiently achieve high Quasi Random Signal (QRS) complex detection accuracy of 91.32%, and assist daily-life ECG monitoring. Recently, more studies have been implemented to improve the artefacts reduction and high-complexity of the ECG data. Hence, a low-complexity ECG compression technique was adopted to improve the use of ECG sensors in remote healthcare monitoring (Elgendi, Al-Ali, Mohamed, & Ward, 2018). This study achieved high QRS detection accuracy of 99.90% and a +P of 99.56% using the MIT-BIH arrhythmia and QT databases. In addition, Mena et al., (2018) developed an ECG monitor which is an integration of a self-designed wearable wireless sensor for detection, prevention, early diagnosis, and treatment of cardiac abnormalities in the home or remote areas. Furthermore, several studies have utilised the ECG sensor for total health monitoring wellbeing. For example, a single chip-based wearable wireless electrocardiogram monitoring system was developed to collect vital real-time ECG data to monitor human heart activity (Sodhro, Sangaiah, & Pirbhulal, 2018). Also, blood pressure estimation was implemented with only ECG signals which provided excellent results close to that of certified medical experts for blood pressure estimation (Simjanoska, Gjoreski, Gams, & Bogdanova, 2018). ECG sensor is applied for detection of various cardiovascular-related health challenges such as breath rate disorder (Nam, Kong, Reyes, Reljin, & Chon, 2016), heart rhythm (Poplas & Stani, 2016), heart diseases (Deshpande & Kulkarni, 2017), and respiratory rate complication (Wannenburg et al., 2018).

(b) Accelerometer sensor

An accelerometer (Zhou, 2020) is the type of homogenous sensor that measures the human acceleration of force and dynamically assesses muscle movements. The accelerometer is predominantly classified into angular *accelerometer* sensor which is improved by angular velocity sensor, and *linear acceleration* sensor which maintains the principle of inertia (balance of forces). The accelerometer is essential for health monitoring especially in human activity identification, sports activities monitoring, energy expenditure estimation, and posture monitoring. Also, the accelerometer sensor provides other functions such as detection of sudden falls in the elderly, and analysis of body motion. In addition, the accelerometer sensor is significant for the well-organized monitoring of other large health conditions. In recent years, there has been a surge of interest in utilizing accelerometer sensors by different studies for effective health monitoring implementation. For instance, Juen, Cheng, Prieto-Centurion, Krishnan, & Schatz, (2014) developed GaitTrack mobile-based application using only an accelerometer sensor embedded in a smartphone to monitor walking patterns, health status, and record spatiotemporal motion. This mobile application achieved 89.22% accuracy without using integration with external sensors. Also, similar methods were used to implement smartphone-related modest ecological momentary assessment (EMA) using smartphone device usage logs embedded with accelerometer sensors (Asselbergs, Ruwaard, Ejdys, Schrader, & Sijbrandij, 2016). Recently, Spinsante et al., (2016) proposed an accelerometer-based human activity recognition system to effectively identify walking patterns in office environments to reduce sedentary lifestyles. The proposed method achieved over 99% accuracy. Furthermore, the accelerometer sensor has recorded an impressive improvement in reducing home calls for professional clinical assistance with regards to neurological disease patients such as multiple sclerosis (Kuusik, Alam, & Kask, 2018). In a similar vein, elderly people between 65 years and above have experienced falls which are the major regular causes of injury and lead to deaths. Hence, researchers investigated efficient mechanism to detect fall in the elderly using accelerometer sensor (Lee et al., 2018). Human motion state recognition such as walking and running was also effectively monitored using a tri-axis accelerometer sensor. In addition, accelerometer sensors played a pivotal role as an integral part of personal health tracking scenarios through the utilization of smartphone built-in accelerometers. In this case, an accelerometer sensor was used to calculate pulse transit time, to estimate blood pressure through measurement of seismocardiography, and the smartphone's camera to measure photoplethysmogram (Sahoo, Thakkar, & Lee, 2017).

(c) Electroencephalography sensor

The electroencephalography (EEG) sensor (Krishna, Carnahan, Co, Yan, & Twefik, 2020) measures the electrical exercise of the human brain. Electroencephalography is non-invasive in nature, hence, the electrical activities of the human brain are continuously measured and monitored through scalp wearable devices. Therefore, an EEG sensor is essential in measuring cortical activities through the placement of electrodes on the skull, scalp, and other identifiable parts of the brain. The EEG recorded signals are analysed for the identification of health issues such as epileptic seizures, brain injuries, antidepressant treatments, and sleep stage analysis. Moreover, EEG signals are utilised in diverse disciplines such as cognitive psychology and science, neuroscience, and physiological domain which involves a significant amount of data from the brain-generated waves. These waves are in inform of Delta, Theta, Alpha, and Beta wave normally used in developing brain-computer interfaces (BCI) in terms of wearable device design, epileptic seizure identification (Ding, Cao, Qu, Duffy, & Ding, 2020). Various studies have utilized EEG sensors in various aspects of health monitoring. For instance, Jaworska et al., (2019) investigated the integration of electroencephalography with machine learning techniques to predict the antidepressant treatment response using EEG signal features. The EEG features were extracted from Theta and Beta with 88% predicted accuracy. Another recent study through the EEG features developed a recurrent neural network (RNN) to predict acoustic features. This is achieved through the regression model and generative adversarial network (GAN) approach (Krishna et al., 2020). In a similar vein, the user of the smartphone recorded a unique experience in a short scenario through the deployment of an electroencephalography sensor (Ding et al., 2020). This invariably helps designers read the users' perception in a much-targeted manner without any form of interruption. Furthermore, EEG sensor has been deployed in different areas such as sleep stage detection (Zhang & Wu, 2017) and affect state emotion recognition (Xu & Plataniotis, 2016) for effective health monitoring system.

(d) Electromyography sensor

Electromyography (EMG) sensor (Michelsen et al., 2020) observes muscle actions in regular and pathological circumstances. It measures the electric signal from muscular activities such as kicking a football, resting, plantarflexion, treadmill walking, standing, etc. EMG sensor is vital for monitoring the motor nerves during surgical operation primarily for detection of clinically induced nerve damage, and confirmation of the functional status of the nerve. Moreover, EMG signals involve the recording of the bioelectric activity of muscles as a sign of neuromuscular stimulation, and electrical variations are mostly experienced in related skeletal muscles, and cerebral palsy. It is designed to study deep muscles that involve a small cross-sectional area of the body. Over the years, various studies have been conducted with electromyography sensors for effective health monitoring of muscle-related activities. For instance, Lim, Tsai, & Chen, (2020) implemented a muscle sense (MS) mechanism which senses and estimates workload exercise during training by utilizing a surface type of electromyography (sEMG) sensor and machine learning models. The outcome of the system shows the capability of EMG to predict workload at acceptable accuracies with minimal errors. In addition, wearable textile type of EMG signals was recently deployed to allow several hours of recording of regular muscle activity and cerebral palsy of children's daily life activities (Michelsen et al., 2020). Moreover, Sener, Martinez-Thompson, Laughlin, Dimberg, & Rubin, (2019) evaluate and record the patient envisaged with myopathies disease. The experiment showed the impact of using EMG to effectively detect pathologic changes in muscle biopsy of the suspected patients. Also, electromyography signals have been deployed to examine various hamstring muscular activities such as high-speed running, bent-knee bridge, prone leg and slide leg curl, straight-knee bridge, and upright hip extension conic-pulley (Hegyi, Csala, Péter, Finni, & Cronin, 2019).

(e) Global positioning system sensor

Global positioning system (GPS) sensor (Difrancesco et al., 2016) which receives from satellite-based navigation approach using the antennas with up to 24 satellites in orbit are deployed to provide the location, effectiveness information, and velocity. With the aid of a GPS sensor, we can trace or locate the nearest healthcare centres or providers for further medical assistance. GPS sensor has also played vital roles in contact tracing, and enforcement of social distancing by the government. For instance, GPS was deployed to trace the location of primary and secondary contacts as governments struggled to manage deadly viruses, which include: novel coronavirus (COVID-19) (Tao et al., 2020), Ebola virus disease (EBOV) (Jacob et al., 2020), and other infectious diseases. GPS sensor also helps in data collection in a remote location, for example, GPS trackers embedded in smartphones provide high-resolution geolocation data for rescue operation in hazardous environments. Moreover, GPS sensor has been utilized to monitor and improve human health and healthcare provider. For instance, Szanto, Benko, Jakab, Szalai, & Vereczkei, (2017) detect and assess early lung cancer using smartphone applications embedded with GPS sensors from wide testing population-based geographic localization of the high-risk group. The smartphone application was downloaded 13,890 times and cover 89,500 smokers within 86 weeks resulting in 30,072 moderate and 10,740 high-risk users. Sequel to this effect, another study utilized a GPS trajectory sensor to leverage non-invasive mobile sensing technology to assess the social anxiety of students during examination (Y. Huang et al., 2017). The location students (no') visited and its transition was able to be collected using the mobile sensing phone. Furthermore, GPS sensor features such as location variance, entropy, and circadian movement offer a lot of hope in detecting depressive symptom from the generated data using the smartphone sensor (Saeb, Lattie, Schueller, Kording, & Mohr, 2016). The GPS features correlated with Patient Health Questionnaire 9-item (PHQ-9) scores of r's ranging from −0.43 to −0.46, and p-values < 0.05). The GPS sensor is applied to recognize patients with Schizophrenia challenges (Difrancesco et al., 2016). Schizophrenia is commonly associated with experiences such as hallucinations, delusions, and confused thinking faculty.

(f) Photoplethysmography sensor

Photoplethysmography (PPG) or Photoelectric sensor (Roy & Gupta, 2020) measures blood volume changes in marginal body parts with the help of optical sensors. It is a wearable biosensor device employed with a light-based technology to sense the rate of blood flow as controlled by the heart's pumping action. Moreover, PPG is used to measure the volumetric variation of blood circulation. The advances in technology have led to the need to develop and extract data from wearable sensors that can capture and process bio-signals produced by the human body. PPG sensor has been widely used in recent years in human health monitoring and clinical trial because of its non-invasive nature. These include measuring the volumetric variation of blood circulation, heart rate variability (HRV), and tracking light physical exercise. Various studies have deployed PPG sensors for effective health monitoring, healthcare service delivery. For instance, Dey, Bhowmik, Sahoo, & Tiwari, (2017) proposed a smartwatch embedded with a PPG sensor for alertness estimation, and sleep management. The proposed system achieved 80.1% accuracy for sleep/awake in alertness score. Also, Essalat et al., (2016) developed a PPG sensor integrated with an acceleration signal for heart rate tracking during physical exercises using a neural network.

(g) Pulse oximeter sensor

Pulse oximeter sensor (Janani, Palanivelu, & Sandhya, 2020) is a non-invasive method of monitoring patients with various degrees of diseases and health issues. It calculates the vital parameters of the patients' body and stores the information using Arduino mega which can be read as beat traces. Therefore, the pulse oximeter sensor uses an electronic processor and a pair of small light-emitting diodes (LEDs) facing a photo-dioxide through a translucent part of the patient's body, usually a finger or an earlobe. Moreover, Pulse oximeters embedded in smartphone applications provide portable, and cost-effective services for health monitoring. For instance, a camera-based application (CBA) that uses a phone camera flash and lens, and a probe-based application (PBA) that uses an external plug-in probe were recently developed for monitoring pediatric patients (Marino et al., 2019). In addition, in advanced pulse oximetry, the practical application of this technique is utilised in a non-invasive sensor to measure oxygen saturation and pulse rate, among other physiological parameters. Pulse oximetry relies on a sensor attached externally to the patient to output signals indicative of various patients' physiological parameters, such as blood constituents, arterial oxygen saturation, among other physiological parameters (Harris et al., 2019). The main components of a pulse oximetry system generally include a patient monitor, a communications medium such as a cable, or a physiological sensor having one or more light emitters and a photo-detector. The sensor is attached to a tissue site, such as a finger, toe, earlobe, nose, hand, foot, or other site having pulsatile blood flow which can be penetrated by light from one or more emitters (Mair, Ferreira, Ricco, & Nitzan, 2020). Most notably, Harris et al., (2019) evaluated various pulse oximeter sensors monitoring of hypoxemic infants with cyanotic heart diseases. The study utilized food and drug administration (FDA) approved handy pulse oximeter, and the hospital-grade pulse oximeter, both types of oximetry achieved high accuracy. Similarly, a pulse oximeter was deployed in dental pulp disease diagnosis (Janani et al., 2020).

(h) Pedometer sensor

A pedometer sensor (Beevi, Miranda, Pedersen, & Wagner, 2016) is an electromechanical device normally deployed for physical activity monitoring, and step counting in combination with motion sensors. It counts the necessary steps a person takes by detecting the hand movement or the pedestrian's hips. Moreover, a pedometer sensor is used to determine the slow walking speed, gaits. It also performs inactivity monitoring such as track movement with some degree of sensitivity. In this case, pedometer sensors are used to count the number of steps covered by the users, monitor the heart rate and walking speed in order to estimate the number of calories burnt by the user. Pedometers have also been implemented for patients that suffer lower extremities during surgery (Beevi et al., 2016). For instance, Beevi et al., (2016) evaluated the accuracy of different commercial step counters based on pedometers such as Yamex (YM), Omron (OM), and Fitbit (FB). The pedometer sensor was deployed for the identification of physical activities such as slow and fast walking when the sensor is placed in the waist location. However, more evaluation is required by placing the pedometer in other locations such as the ankle, chest pocket, and neck to provide comprehensive evaluation, and generalization of the results obtained. Furthermore, the medical community and other health professionals implement pedometer sensor devices to access the level of physical activities required by individuals. For example, a pedometer sensor was deployed in feedback during cardiac emergency conditions detection (Nair, Kumar, A, Mohan, & Anudev, 2018).

(i) Temperature sensor

Temperature sensor (Trung, Ramasundaram, Hwang, & Lee, 2016) measures the amount of heat energy or coldness that is generated by an object, thereby allowing the user to detect any physical changes to the objects. Temperature sensors are in form of digital or analog sensors. Digital temperature sensor maintains a linear solution which eliminates the requirements for complex calibration and design, unlike analogy sensor. There are various areas of health monitoring where temperature sensor has recorded impressive performances. For instance, in a smartphone-based driver safety monitoring system using data fusion, the temperature sensor was deployed in the steering wheel as well as on the skin (Lee & Chung, 2012). In addition, the temperature sensor has been utilised in different areas based on its usability. Trung et al., (2016) developed an all-elastomeric transparent and stretchable temperature sensor for body-fix wearable electronics. This was widely applied in health monitoring, robotics, human-machine interfaces, and artificial skin. In addition, the integrated sensors were practically utilised by attaching the patch to a human body and simultaneously monitoring temperature changes, and muscle movements during the activities of drinking hot water and working out.

3.2 Dual sensor

The health monitoring systems categorised as dual sensor-based are studies that utilized two sensors modules for various health monitoring researches. In our broad review, we discovered that different studies combine a two-sensor model to implement a cost-effective health monitoring system. The use of multiple sensors helps to minimize the effects of indirect sensor capture. In addition, the dual sensor model provides reliability, credibility, and better accuracy especially when deployed to monitor multiple health parameters (Nweke et al., 2019). Among the studies reviewed, sensors that were predominantly integrated for health monitoring include accelerometer, gyroscope, ambient sensors, Electrocardiography, Photoplethysomography sensor, and ECG for activity displacement detection, mental disorder diagnosis and to monitor heart rate variability. Consequently, studies that implemented dual sensors for various health monitoring applications are discussed below.

(a) Accelerometer and gyroscope sensor

Even though the accelerometer sensor provides efficient means to monitor activity levels, postures, and energy expenditure during strenuous exercise, it has some limitations that can be corrected when integrated with other sensors. It is difficult to detect posture in real-time with only accelerometer sensors. Moreover, a single accelerometer sensor is ineffective to discriminate between dynamic motions or activities with similar patterns (Nweke et al., 2019). A recent study proposed a health monitoring system that integrated accelerometer and gyroscope sensors to analyse body orientation, detect activity displacement, and step count based on the user activities (Acharya et al., 2019). Other researchers have also proposed different fusion models to combine accelerometers and gyroscopes for health monitoring. For instance, Canzian and Musolesi, (2015) developed a mobile phone-based application to monitor depressive mood disorder (DMD) in patients by leveraging accelerometer and gyroscope sensors. This study analyses the movement pattern and depressive mood of the patients in order to provide timely intervention strategies. A recent study by Hakim, Huq, Shanta, & Ibrahim, (2017) designed and analysed human fall detection mechanism with smartphone embedded inertial sensors (e.g. accelerometer and gyroscope sensors). The authors achieved up to 99% accuracy they utilized sensor parameters such as acceleration force, angular velocity, and sensor orientation. In addition, accelerometer and gyroscope sensors have also played pivotal roles in concurrent human activity recognition, walking-age pattern analysis and identification (Jin et al., 2014), social rhythms in bipolar disorder evaluation (Abdullah, Matthews, Frank, Doherty, & Gay, 2016), and diagnosis of a chronic auto-immune disorder of the central nervous system (sclerosis diseases) (Gong, Qi, Goldman, & Lach, 2016).

(b) Accelerometer and Ambient sensor

Accelerometer and ambient sensors are commonly combined to implement comprehensive health monitoring, status health check, diagnosis and treatments of illness, and health tips for general wellbeing. For instance, Ben-zeev, Scherer, Wang, Xie, & Campbell, (2015) used a multimodal smartphone embedded with an accelerometer and ambient (photodetector) sensor to assess behavioural markers for people with mental health issues. Hence, the study achieved early detection of psychiatric (mental disorder). Also, breath disorders (Cardiovascular disorder) such as chronic obstructive pulmonary disease (COPD), asthma, and pneumonia have been diagnosed and managed with the aid of accelerometer and ambient sensors (Stafford, Lin, & Xu, 2016).

(c) Electrocardiography and Photoplethysmography sensors

The integration of Photoplethysmography (PPG) and electrocardiography (ECG) sensors are compatible for monitoring an individual's health. For example, (Bánhalmi et al., 2018) developed an iPhone application embedded with dual sensors to compare pulse rate variability (PRV) and heart rate variability (HRV). The regular health status of individual suffering from the heart-related disease is determined through HRV because it maintains variation between consecutive hearts beat and show the activity of the autonomic nervous system (ANS). Smartphone flash and camera help to measure the PRV. The signal of PPG reflects through the illumination of the skin using an LED. Therefore, it provides a good correlation between PRV and HRV, hence, both are well utilised for effective health monitoring systems.

(d) Photoplethysomography and Accelerometer sensors

Photoplethysmography and accelerometer sensors provide dual signals to monitor and check health status, detect early negative health conditions, and ensure comprehensive health management of the elderly populations. To this effect, Yu, Chan, Zhao, & Tsui, (2018) implemented an integrated and efficient platform mechanism for effective monitoring wellness of elderly people in Hong Kong metropolis using the PPG and accelerometer sensors. The implemented system also helps for effective data sharing, prediction, and decision-making processes.

(e) ECG and SCG sensors

Electrocardiography (ECG) and seismocardiography (SCG) sensors are utilised to detect cardiovascular (CAD), and other health-related conditions. CAD has become a life-threatening disease that causes sudden death. The deaths are a result of sudden health attacks and brain strokes associated with coronary heart disease (CAD), and cerebrovascular disease respectively. Based on the devastating effects of the disease, researchers have proposed various technology-based approaches for its early diagnosis and treatments. Of the major approaches is the use of sensors to analyse physiological signals and provide an early warning (Sahoo et al., 2017). In this case, ECG is used to measure the heart rate while SCG measures the translational, and rotational cardiac vibrations prompted by left ventricular motions. Also, Iftikhar et al., (2018) developed a multi-channel mechanism that integrated ECG and SCG data analysis for cardiac early warning monitoring systems using a smartphone application. The smartphone installed with mechanocardiography runs on the screen after capturing the body physiological signals for self-monitoring, and detection of cardiovascular health-related diseases. A recent study by Abdulghaffar, Mohammad, Ammar, Tarek, & Elhadi, (2019) implemented an Internet of Things (IoT) based technology using CISCO packet tracer tool for monitoring multiple diseases such as glaucoma, hypertension, and chronic obstructive pulmonary diseases. This was achieved through ECG and SpO_2 (Oxygen saturation). Health care provider and mobile user connect to the developed system through the cloud (internet), hence, utilized for disease diagnosis in the healthcare centre for improved health care services.

(f) ECG and EEG sensors

ECG and EEG sensors are responsible for cardiac related activities and brain functionality behavior. These sensors are very complementary. Effective utilization of the sensors is essential to monitoring brain abnormality and heart-related diseases such as CAD and arrhythmia. For instance, Mishra, Gautier, & Glasscock (2018) utilizes the ECG and EEG sensors to detect and monitor brain to heart simultaneously with neuro-cardiac dysfunction in mouse models of epilepsy. Also, ECG and HR (heart rate) sensors are deployed for cardiac associated with rehabilitation (Etiwy et al., 2019). Furthermore, the patient's vital signs such as body temperature, heart rate, and blood pressure were monitored with a blood pressure and temperature sensor (Swaroop et al., 2019). More so, neurodegenerative disorder (e.g. epilepsy) was detected using smartphone built-in ECG and EEG sensors (Subasi et al., 2020).

3.3 Heterogeneous sensors

By Heterogeneous sensors, we mean the integration of diverse multiple sensors for effective implementation and deployment in human health monitoring systems. In most of the studies reviewed, we discovered that various studies combined multiple sensors in order to resolve some issues inherent in the use of a single sensor for all-inclusive health monitoring. The use of a single sensor for health monitoring has peculiar issues integrating comprehensive services such as health status checks, diagnosis, treatment, prevention, rehabilitation, recommendation, and decision-making in order to achieve optimal healthcare monitoring. Therefore, attaining vitality of the general wellbeing can be realized through multi-sensors. Multiple sensors usage can also give a holistic approach to provide a solution to various healthcare challenges ravaging society. Various authors have demonstrated promising research studies where these sensors have recorded an impressive performance through the provision of solutions to different healthcare problems. To this effect, Lee, Robinovitch, & Park (2014) achieved near-fall detection regards to activities of daily living (ADLs) by integrating multiple motion sensors (accelerometer, gyroscope, and magnetometer). The magnetometer is an inertial measurement-based sensor primarily deployed to ascertain the relative changes and variation in the magnetic field in a particular direction, hence, it is combined with gyroscope and accelerometer sensor to achieve high rate accuracy fall detection and recoverable imbalances (near-falls). Also, the tri-inertial sensor was used to implement a single body-worn wireless inertial node directly fixed on the patient's chest (Giuberti et al., 2015). The developed system was used to detect Parkinson's diseases (diseases associated with disorder of central nervous system which result in awkward movement and tremor). Similarly, accelerometer, acoustic, GPS, light sensors were built-in with smartphone sensing systems to detect people associated with schizophrenia illness (complex psychiatric disorder) (Wang et al., 2016).

Moreover, multiple sensors such as accelerometer, GPS, gyroscope, magnetometer, proximity sound, phone call log sensors embedded in smartphones were recently deployed for monitoring of psychiatric or bipolar disorder (Gr et al., 2014). The features of this system achieve accuracies of 76% by combining various sensor modalities and state change detection evaluation performance matrix of over 97%. Also, depressive symptoms from daily life behaviour were detected using the same smartphone fused with all sensor modalities such as accelerometer, GPS, gyroscope, magnetometer, proximity sound, phone call log (Saeb et al., 2015). More so, multi-modal sensors such as accelerometer, gyroscope, magnetometer, pulse oximeter, blood pressure, and ECG were implemented using IoT-based mobile phones for monitoring human biomedical signals for physical exertion (e.g. athletes). The proposed system is essential to predict likely injuries and possible sudden death (Mora, Gil, & Szymanski, 2017). Also, motion and ambient sensors such as gyroscope, temperature, and proximity sensor were used in an ambulatory health monitoring system. The system was implemented through communication channel enabled IoT which helps to reduce the system complexity and power consumption (Sundaravadivel, Mohanty, Kougianos, Yanambaka, & Thapliyal, 2017).

In another related study, Kakria, Tripathi, & Kitipawang, (2015), developed a low cost-effective system using smartphones fused with pulse rate, blood pressure, and body temperature sensors to monitor patients' cardiac diseases, hypertension, diabetes, etc. They noted that the system is capable of alerting the doctor and patient under severe health circumstances through warning messages. In addition, diagnosis of cardiovascular-related diseases such as heart attack, hypotensive, stroke, etc. recorded impressive performance through the fusion of three sensors such as impedance cardiogram (ICG), ECG, and PPG (Du, 2016). Also, multiple sensors such as PPG, heart rate, SPO_2, blood pressure, and temperature sensor were recently implemented on-board smartphones for diagnosis of diseases, and stress management (Wannenburg & Malekian, 2015). The system measures the accuracy of the multi-modal sensors thereby providing the user with feedback mechanisms through mobile-based unit message notifications to medical health workers or doctors on the ground to ensure effective health monitoring. A further earlier study by different authors utilise heterogeneous sensors for monitoring of general wellbeing. For example, prediction and diagnosis of disease using fog assisted IoT in severe diseases cases. The study utilized fusion of three sensors such as blood pressure, ECG, and EEG sensors (Verma, Sood, & Sood, 2017), which was deployed to monitor the health status of pregnant women (Santhi, Ramya, Tarana, & Vinitha, 2017).

Recently, various authors have also utilized heterogeneous sensors for both diagnosis, detection, and general health monitoring system of an individual. For instance, Nedungadi et al., (2018) performed differential diagnosis and monitoring of patients physiological parameters in the local language, provided personalised guidance, and alerted mechanism between patient-centric system and the healthcare providers or doctors through the integration of blood pressure, ECG, pulse rate, body temperature, and oxygen sensors. The survey feedback from the community it was deployed indicates that 82% of patients were able to straightforwardly operate, and know the guidance delivered by the system. In addition, about 94% of the patients found the system worthy to provide personalized feedback to patients. Also, accelerometer, gyroscope, and magnetometer were combined to monitor physical activities such as climbing stairs, cycling, the frontal elevation of arms, lying down, sitting, relaxing, standing, walking, etc of elderly people using the internet of medical things (IoMT), and intelligent approach to enhance treatment recommendations (Syed, Jabeen, & Alsaeedi, 2019). Also, Al-khafajiy et al., (2019) developed a smart healthcare monitoring system using pulse rate, oxygen, heart rate, and blood pressure sensors integrated into Raspberry pi to detect physiological disorders of elderly patients remotely which could aid early intervention practice. The authors noted that the implemented smart healthcare system is cost-effective when evaluated with data acquisition from experiments. Bedridden patients were monitored with similar multi-sensors such as ECG, EMG, temperature, humidity, and heart rate sensors (Debauche, Mahmoudi, Manneback, & Assila, 2019).

Furthermore, Dur, Santana-mancilla, Buenrostro-mariscal, Montesinos-Lopez, & Estrada-Gonzalez, (2019) developed a mobile-based application built-in with multi-sensors such as heart rate, body temperature, and blood oxygenation sensors for health monitoring. The system monitors the health status of older adults residing in the rural environment. In addition, the smartphone applications and multiple sensors were dedicated to health monitoring which were interconnected with IoT to ensure effective communication and data transmission. For example, through IoT, mobile healthcare applications were connected with multi-sensors such as PPG, ambient temperature, relative humidity CO_2, body temperature, and ultra violet sensors to remotely monitor human health environmental hazard safety (Wu, Wu, & Yuce, 2019). Recently, human activities recognition such as running, sitting, walking, standing, climbing etc. were analysed to ensure absolute health monitoring through IoT integrated with sensors such as heart rate, pulse oxygen saturation level (SPO_2), and temperature sensors (Thaung, Tun, Kyu, Win, & Than, 2020). Some of the features, strengths and weaknesses of the sensors discussed above are presented in *Table 3*.

Table 3. Various sensors for human health monitoring; descriptions, strengths, and weaknesses.

Sensor type	Sensor	Description	Strength	Weakness	References
Homogeneous sensor	ECG	Provide valuable information about the cardiovascular system using evaluating electrical heart-related activity	It facilitates health care cost reduction, early release from hospitals, reduced pressure on health care providers, and accessibility to care for underserved populations in remote areas	It reveals the heart rate and rhythm only during the few seconds it takes to record the tracing. Abnormalities turn out to have no medical significance after a thorough evaluation is done	(Deshpande & Kulkarni, 2017; Elgendi et al., 2018; Lee et al., 2014; Mena et al., 2018; Nam et al., 2016; Neyja, Mumtaz, Mohammed, Huq, & Busari, 2017; Poplas & Stani, 2016; Simjanoska et al., 2018; Sodhro et al., 2018; Wannenburg et al., 2018)
	Accelerometer	Uses acceleration force of the body to measure human motion.	Has low power consumption and enables continuous monitoring of human behaviours.	Unable to detect posture in real-time, and correlation posture and action	(Asselbergs et al., 2016; Juen et al., 2014; Kuusik et al., 2018; Lee et al., 2018; Spinsante et al., 2016; E. J. Wang, Zhu, Jain, Lee, & Saba, 2018; X. Zhou, 2020)
	EEG	It is a device that measures the potentials of electrical exercise of the human brain.	It is non-invasive in nature, measure the cortical activity without surgery through the placement of electrodes on the skull, scalp, and other parts of the brain.	It requires complex data analysis, signal processing, and annotation process	(Ding et al., 2020; Jaworska et al., 2019; Krishna et al., 2020; Xu & Plataniotis, 2016; Zhang & Wu, 2017)
	PPG	Evaluate the volumetric changes of the heart by measuring light transmission using electrical signals.	Helps in optical detection of blood volume changes in the micro-vascular bed of the tissue, hence, less influenced by the tissue and vein region	Require a relatively long setting time and often peak interval accuracy is limited by usable sampling rate due to the high power consumption of LEDS	(Dey et al., 2017; Essalat et al., 2016; Roy & Gupta, 2020)
	GPS	Receiver from satellite-based navigation approach to provide the location, useful information, and velocity.	Improve detection of geolocations visited, direct high-risk group to the nearest screening centre, and early warning	Inconsistencies data collection process and depends on user's compliance.	(Difrancesco et al., 2016; Y. Huang et al., 2017; Saeb et al., 2015; Szanto et al., 2017)

Sensor type	Sensor	Description	Strength	Weakness	References
Homogeneous sensor	EMG	Examine muscle activities, diagnose, and evaluate peripheral neurological disorders	Convey information related to the peripheral nervous system and nerve conduction for an effective health monitoring system	Limited diagnostic for clinical trials and lack of cooperation among the patients	(Hegyi et al., 2019; Lim et al., 2020; Michelsen et al., 2020; Sener et al., 2019)
	Pedometer	Device for activity monitoring. It is also used to calculate the no of calories burnt and the number of steps taken by a user. It measures common activity.	They are inexpensive and non-invasive. Lower blood pressure and blood sugar control, cholesterol level bone density improvement and lower the risk of cancer.	Lack of a standard protocol and making comparison difficult and error prone. The accurate result is not maintained	(Beevi et al., 2016; Nair et al., 2018)
	Temperature	It measures the amount of heat or even the coldness generated by an object or system	Reference temperature not required. Rugged, inexpensive wire	Require accurate reference temperature, Expensive wire. It required much power	(Trung et al., 2016)
	Pulse oximeter	It is a device intended for non-invasive measurement of arterial blood oxygen sutured (spo2) and pulse rate	It is non-invasive, simple and can be used to evaluate trends (evaluation of oxygenation during exercise, and during procedure	The device is delicate, sensitive to handle, and possess excessive heat	(Harris et al., 2019; Janani et al., 2020; Mair et al., 2020)
Dual sensor	Accelerometer and gyroscope	Measure body acceleration and angular rate or change in rotational angle per unit of time	Maintain concurrent human activity recognition and analyse the movement of the depressive mood, thereby offering quick response rate	Difficult to detect the correlation between the posture and actions in real-time	(Canzian & Musolesi, 2015; Jin et al., 2014)
	Accelerometer and ambient sensor	Combine acceleration and photodetector of different physiological parameter for health monitoring	Offer health check, diagnosis, and recommend treatment or health tips for general wellbeing	Finest mental health wellbeing might not be attained. Smartphone sensing creativity needs more assessment and features	(Ben-zeev et al., 2015)
	Accelerometer and PPG	Tracking the vital signs, detecting body present	Enable data sharing, prediction and for the effective decision-making process.	Require wide rang testing to detect the health status of elderly	(Yu et al., 2018)

Sensor type	Sensor	Description	Strength	Weakness	References
		changes and predicting health risks		both in day care and other health challenges	
	ECG and PPG	Maintain variation between consecutive heartbeats and show the activity of the autonomic nervous system	Good correlation between pulse rate variability (PRV) and heart rate variability (HRV) for health checks.	Require deeper analysis of the ECG channels	(Bánhalmi et al., 2018)
	ECG and SCG	Measure the heart rate carry out translational and rotational cardiac vibrations	Perform disease screening and detection of the cardiovascular (CAD) health-related condition through an early warning mechanism	Limited in controlled blinded tests and application usage in distribution	(Iftikhar et al., 2018)(Sahoo et al., 2017)
	ECG and SPO_2	The two sensors are combined for efficient health monitoring of diseases	Enable monitoring of multiple diseases	Require improvement to support a variety of heterogeneous diseases	(Abdulghaffar et al., 2019)
	ECG and HR	Focuses on the heart's electrical system to detect heart-related diseases	It is simple, safe, inexpensive to use, and covers a large diversity of cardiac issues	Heart disease such as CAD may appear nearly normal, takes only a few seconds to record the tracing of heart rhythm. Also, abnormality might occur	(Etiwy et al., 2019)
	ECG and EEG	Concentrated on cardiac activities and brain behaviour	Monitor patients cardiac rhythms and abnormal brain functionality	Variability and lack of standardisation of sensor features, and individual of the patterns	(V. Mishra et al., 2018; Subasi et al., 2020)
	Blood pressure and temperature	Patient's basic health parameters such as body temperature, heart rate, blood pressure, and temperature.	Reduce delay in the clinical trial and health checks for patients. Also, restore confidence and offer multimodal feedbacks	Changes in the body system affect the usage of the sensors and network connectivity. Also, affect the data storage and analysis of data through IoT devices	(Swaroop et al., 2019)
	Accelerometer, GPS, gyroscope, magnetometer,	Involves daily life behavioural patterns	Identifying early state change, depressive symptoms harshness, behavioural	It doesn't support so many periods of training and calibration	(Gr et al., 2014; Saeb et al., 2015)

Sensor type	Sensor	Description	Strength	Weakness	References
	proximity, sound, and phone call log	monitoring in terms of depressive symptoms	markers, and patient at-risk population are often monitored		
	Accelerometer, gyroscope, and magnetometer	Involves fall and activities of daily living and kinematic features assessment	Maintain the effects of gravity and independent orientation and for a health check	Energy consumption is high thereby constituting degradation in performance	(Giuberti et al., 2015; J. K. Lee et al., 2014)
	Pulse rate, blood pressure, and body temperature	General remote monitoring of cardiac patients wellbeing	Checkmate the healthcare utilization cost, deployment, accuracy, and data security for patients to doctor communication	High integration cost, offsite diagnoses, and communication connectivity	(Kakria et al., 2015)
	PPG, heart rate, SPO_2, blood pressure, and temperature	Measure and interpret the essential physiological parameters and signals, and monitor biofeedback of the user	Improve the physiological parameters and prove optimal health monitoring, and enhance the effective feedback from the user to the medical health giver	Influence by external factors based on the size such as skin temperature, perfusion, and pigmentation	(Wannenburg & Malekian, 2015)
	Accelerometer, acoustic, GPS, and light sensor	Monitoring mental health and general functioning in an individual with schizophrenia	Predict and detect early mental health illnesses such as schizophrenia for real intervention	Low adherence, and passively in new sensing and detection of mental health disorders using smartphones in the market	(R. Wang et al., 2016)
Heterogeneous sensor	ECG, ICG, and PPG	Asses the cardiovascular status of patients	Generally assess, detect and monitor the patient's parameter for cardiac health status	High-speed energy is required, and attenuation occurs at an interval	(Du, 2016)
	Blood pressure, ECG, and EEG	Focus on diseases diagnosis and prediction	It facilitates user diagnosis results with regards to the health history measurements	More versatile cloud-based IoT disease diagnosis requires better health monitoring	(Verma et al., 2017)
	Temperature, pulse rate, pressure, and heart rate	Total health check-up especially during pregnancy	Offer early and regular check-ups for pregnant women, and monitor the physiological parameter such as heartbeat and temperature	Relative cost and high power consumption	(Santhi et al., 2017)

Sensor type	Sensor	Description	Strength	Weakness	References
	Accelerometer, gyroscope, magnetometer, pulse oximetry, ECG, and blood pressure	Describe the activities involving human biomedical signals with regards to physical activities such as sports, movements, and other exercises	Improve system rehabilitation and provide enough patient physiological parameter information	High processing power, offline analysis challenges and require advanced analysis of the health status monitoring information collection and processing	(Mora et al., 2017)
	Temperature, proximity, and gyroscope	Involve trajectory IoT ambulatory health monitoring system	Provide human body ambulatory health monitoring and communication	Power utilization affected and data acquisition challenges due to network communication	(Sundaravadivel et al., 2017)
	Blood pressure, ECG, body temperature, pulse rate, and oxygen	Monitor mental health and general wellbeing of people in rural-based areas	Provide remote real-time health monitoring of patients in rural areas	Affected by network accessibility and power consumption	(Nedungadi et al., 2018)
	Accelerometer, gyroscope, magnetometer, and ECG	Monitor physical activities of elderly people	Provide optimal smart monitoring of the health challenges of older people based on their physical activities	Require advanced IoMT connectivity of devices to provide efficient health monitoring and data analysis	(Syed et al., 2019)
Heterogeneous sensor	ECG, EMG, temperature, humidity, and heart rate	Assess patients movements and health monitoring of the elderly people based on their physiological and environmental parameters	Monitor the human health status and behavioural change of the elderly people	High energy utilization, privacy issues, cross information mismatch, and data anonymization of patient data	(Debauche et al., 2019)
	Pulse rate, oxygen, heart rate, and blood pressure	Remote health checks of elderly people	To track a person's health physiological data in order to detect and ascertain their health status to guide early intervention practices	Data anonymization and transmission from patient's location to the doctor issues	(Al-khafajiy et al., 2019)
	Heart rate, body temperature, and blood oxygenation	Monitoring of elderly people using IoT based systems including mobile apps	Monitor an aged (older) people's health who live in remote locality via mobile apps	Network connectivity and transmission challenges, high energy consumption	(Dur et al., 2019)

Sensor type	Sensor	Description	Strength	Weakness	References
	PPG, ambient temperature, relative humidity, CO_2, and ultraviolet	Monitor the health well-being of the individual in the workplace	Collect worker's data and send it to the medical health server for proper data analysis to detect health status and signal to ensure the safety of the workers	Require an enhancement to add the basic functionality for onward transmission and analysis of the worker's health checks	(Wu et al., 2019)
	Heart rate, temperature, and SPO_2	Measured data statistics to ascertain the effective monitoring of human activity using IoT	Ensure testing, collecting health information, and healthcare monitoring of human activities	Network interconnectivity issues require complex data analysis for proper interpretation of the health information collected	(Thaung et al., 2020)

****ECG**(Electrocardiography), **PPG**(Photoplethysomography), **EEG**(Electroencephalography), **GPS**(Global positioning system), **EMG**(Electromyography), **SPO_2**(Oxygen saturation), **SCG**(seismocardiography), **ICG**(impedance Cardiogram)

751

4. System Architecture for Health Monitoring

The system architecture for mobile-based health monitoring depicts a general overview of the components of health monitoring systems. The components involve the processes of collecting data using mobile and wearable sensors, and analysing the collected sensor data for disease diagnosis, detection, and recommendation of treatment procedures. In this section, we discuss these components and their implementation methods. The major components of health monitoring systems include data collection process, data transmission, data integration, data pre-processing or de-noising, data analysis, feature extraction, and finally the evaluation of the developed health monitoring systems. These six components are represented diagrammatically in Fig. 4.

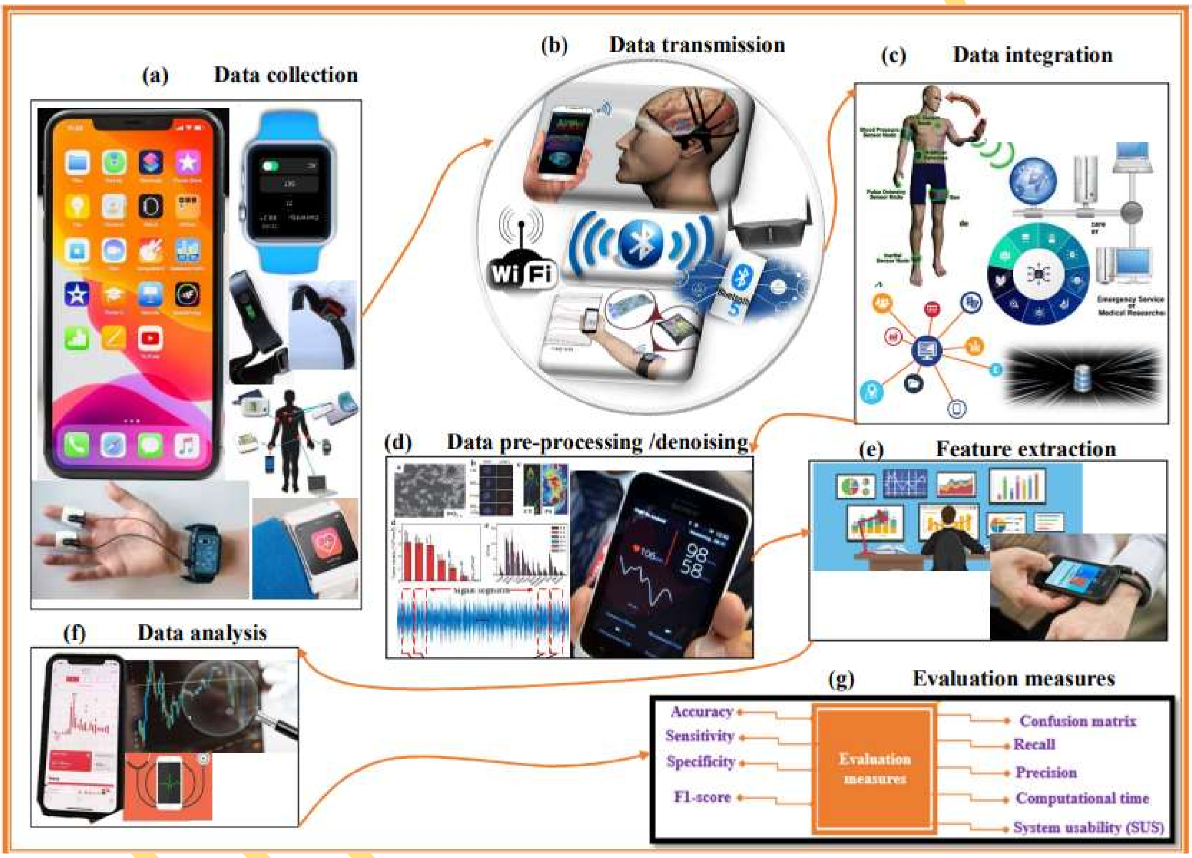

Fig. 4. System architecture for mobile and wearable devices health monitoring.

4.1 Data collection process

This depicts various means through which different authors/researchers collect data for health monitoring system development as shown in Fig. 4(a). We identified four (4) media through which data are collected from different works reviewed. These include smartphone devices, microcontrollers, wearable devices, and questionnaire/interview approaches. All these mechanisms aided the successful implementation of the health monitoring system by the studies. For instance, an earlier study by Juen et al., 2014; Kakria et al., (2015) used smartphone and android handheld phones to collect data from cardiac patients for walking patterns and giant analysis respectively. Also, another related study by Swaroop et al., (2019) utilised Raspberry Pi3 (RRi3) device to collect a patient’s vital signs from the system design. A similar study by Yu et al., (2018) collected data from 11 elderly nurses or nursing mothers aged 65 years old in Hong Kong for 3 months using Sony Smart-brand 2 wellness tracker device and self-reported wellness diaries. Recently, Subasi et al., (2020) utilised smartphones and smart sensors such as ECG and EEG sensors to collect data from patients for medical diagnosis and treatment.

Furthermore, some studies collected via microcontroller CC3200 device interfaced with sensors enabled devices to monitor the health status of pregnant women (Santhi et al., 2017). In sensors-related categories, several studies have been implemented from sensor-generated data for the fully functional mobile health monitoring system. For example, a lot of data were generated from wearable and embedded ECG biosensors from electrical activities such as heart beat, brain signals in the human body system (Neyja et al., 2017; Sahoo et al., 2017; Sodhro et al., 2018). Also, a recent study by (Debauche et al., 2019; Subasi et al., 2020; Syed et al., 2019) utilizes ECG wearable biosensors to collect data from the patient's body system which some of them were fixed, worn, embedded, etc. in the human body. For example, some of the ECG sensors were placed on the right wrist, chest, and left ankle to detect and measure movements by the subjects (Syed et al., 2019). Other sensors used to generate data for health monitoring includes EEG, EMG, blood pressure and body temperature, PPG, and Seismocardiography (SCG). However, various authors have utilized these sensors to collect data in different means, for instance, (Debauche et al., 2019; Subasi et al., 2020; Verma et al., 2017) collected data through EEG, EMG, and SCG for mobile health monitoring development. Some of the biosensors used were either implanted or worn by the patients for detection of various ailments such as infectious disease diagnosis, epilepsy, etc. In addition, a wearable sensor such as Piezoelectric lead zirconate titanate (PZT) was used to collect data for the detection of environmental real-time bolted joints of health workers in harsh weather (Wang et al., 2018). Relatively, studies by (Debauche et al., 2019; Siam, 2019; Swaroop et al., 2019; Thaung et al., 2020) utilise biosensors such as pulse oximeter, blood pressure, body temperature, SpO_2, etc., attached to the physiological body of the patients to capture data for various activities such as standing, running, sitting, etc. and to detect patient's vital sign such as cardiac disorder, high blood pressure, heart attack, etc. More so, data collected from interviews and surveys (Dur et al., 2019; Junde Li, Ma, Chan, & Man, 2019) were utilised to develop a comprehensive assessment of the remote health status of elderly people. The interview was conducted with the elderly and a survey of 146 among the adults between 60 years and above was maintained.

4.2 Data transmission

Data transmission is the process by which data are transferred from the digital devices to another component system for data analysis. For an effective health monitoring system, the collected data are transmitted to the right location or components for further processing and analysis to aid decision-making and implementation. Various modes of transmission of data collected from one system device to another system and the server storage system have been identified by numerous studies. From our extensive review, we identified five (5) vital technologies or forms through which data are transmitted. These technologies include Bluetooth, Wi-Fi/3G-5G network, Short Message Services (SMS), internet-enabled smartphones, serial and parallel transmission. All these mentioned mechanisms assisted immensely in data transmission for the effective implementation of health monitoring systems. Different authors have widely utilised these media for efficient transmission of data during system implementation and deployment for health monitoring and the general wellbeing of people. For instance, the earlier study by Juen et al., (2014) transmitted the extracted data and transferred it to the central database from smartphones such as Motorola Droid Mini, ActiGraph GT3x, and Samsung Galaxy Ace connected with Bluetooth to a Nonin Onyx2 pulse oximeter with heart rate and oxygen saturation to keep monitoring medical alerts. Also, in another related work, the extracted data were transmitted from biosensors to the smartphone through Bluetooth and then to the web server via GPRS/Wi-Fi/3G network (Kakria et al., 2015). More so, a recent study by (Enamamu, Otebolaku, Dany, & Marchang, 2020; Kumar, Lokesh, Varatharajan, Chandra Babu, & Parthasarathy, 2018; Subasi et al., 2020) collected data and then transmitted it to the data storage system using Bluetooth connected to the smartphone. The transfer was also enabled by Wi-Fi/4G-5G communication network (Nweke & Alo, 2013). For example, the hospital data collected was transmitted into the cloud database for permanent storage via 5G mobile networks.

Furthermore, a related study by Siam, 2019; Syed et al., (2019) transferred the collected data through Wi-Fi 802.11 networks on the cloud. Then the data is further transferred to the cloud platform such as Amazon web services (AWS) for advanced data analysis. In addition, the captured data was transferred through the IoT gate or multimodal communication components such as Raspberry Pi (RPi3)'s on-chip BLE CSR 4.0 protocol, Wi-Fi modules and USB ports to the interface General Service Mobile (GSM), internet connection, and a LoRa module (Swaroop et al., 2019; Wu et al., 2019). Some of these collections were stored in big data storage systems such as Apache Kafka for further analysis (Debauche et al., 2019). Also, Mora et al., (2017) utilises sensing devices such as Bluetooth, Wi-Fi, mobile phone, etc. of the body area network (BAN) and wireless local area network (WLAN) to transmit data collected from the cloud computing component with enabled IoT for further data analysis and visualization. However, another author attempted to use a different approach to transmit data. For example, (Nedungadi et al., 2018) transmitted critical patients details through SMS, email, and internet to cloud restful application programming interface to the mobile device and to the doctors for action to be taken. Also, (Thaung et al., 2020) utilise serial transmission to send data collected to the destination. Time is set for one minute for every sensor used such as heartbeat, SPO_2, and temperature sensor. The processes involved, one-minute interval, first heart beat sensor is tested, followed by SPO_2 sensor detection. Therefore, serial port transmissions were utilise in all circumstances. Similarly, Sony Smart brand wellness tracker with an installed sensor was used to transmit data from patients at home in Hong Kong to the telehealth monitoring assessment central database system (Yu et al., 2018). The various data transmission process is shown in Fig. 4(b).

4.3 Data Integration

Data integration is the process of fusing/combining sensor data from varieties of heterogeneous sources into a single complex health monitoring environment. The integration of various data sources aids increased reliability, robustness, and generalization of the health monitoring systems. Furthermore, the data integration process aims to decrease the uncertainty, and the effect of indirect capture that is prevalent in single predictor-based health monitoring systems (Nweke et al., 2019). The data integration process is shown in Fig. 4(c). For instance, Yu et al., (2018) proposed a fusion of total sleep duration, step count, and heart rate variability to monitor the wellness conditions of the elderly in the Hong Kong community. With the proposed health monitoring system, medical practitioners can easily evaluate the elderly activity level and vital signs to give informed decisions and provide appropriate health advice. Also, Al-khafajiy et al., (2019) developed a smart healthcare monitoring system using multi variables such as pulse rate, oxygen, heart rate, and blood pressure sensors integrated with Raspberry pi to detect the physiological disorder of elderly patients remotely which can aid early intervention practice. The implemented smart healthcare system is cost-effective when evaluated with data acquisition and manipulation. More so, bedridden patients were monitored with similar multi-sensor such as ECG, EMG, temperature, humidity, and heart rate sensors (Debauche et al., 2019). Human activities recognition such as running, sitting, walking, standing, and climbing source data generated were analysed to ensure absolute health monitoring through IoT integrated with sensors parameters such as heart rate, pulse oxygen saturation level (SPO_2), and temperature (Thaung et al., 2020).

4.4 Data pre-processing (de-noising)

Fig. 4(d) depicts the methods to pre-process and clean health monitoring related data collected using mobile and sensors. Usually, wearable sensors and other health monitoring trackers have noises, errors, and motion artefacts. Pre-processing or de-noising is necessary before further processing on the data is initiated. There are four major components involved in data pre-processing. These include filtering out unusual data to remove artifacts, interpolating missing sensing data, removing high-frequency noises, and synchronization and normalization of the extracted data (Ikegwu, Nweke, Alo, & Okonkwo, 2021; Uddin, Salem, Nam, & Nadeem, 2015). The statistical technique is widely utilised by various authors in de-noising the collected and transmitted data for further processing. These include Fast Fourier Transforms (FFT), power spectral density (PSD) method, and low/high pass filtering mechanism were implemented by some authors to remove noise in some sensors extracted data before analysis. For instance, recent studies by (Juen et al., 2014; Kakria et al., 2015) proposed a statistical approach such as a regression model to pre-process the data by counting 6mins walk test from congestive heart failure and chronic obstructive disease. Also, Juen et al., 2014; Kakria et al., (2015) utilized mean values to pre-process patients' information such as gender, age, address, etc. In another study by (Essalat et al., 2016) used a high/low pass filter to clean Photoplethysmogram sensor in order to remove artefacts obtained during data collection. The high frequency ranging from 0.8 and 13Hz was removed. The signal was divided into 8s frames using sliding windows which have 6s overlap compared to the initial windows and slides of 2s. Furthermore, sensor data were pre-processed using bilinear transformation in combination with Biquade Direct Form Transposed II and Fuzzy Rule-based Neural Classifier (FRNC) by (Kumar et al., 2018; Sodhro et al., 2018).

Furthermore, a recent study by Enamamu et al., (2020) applied a statistical approach for data processing using feature extraction. Hence, 12 initial subjects were set aside for the test run, then another 12 statistical features were used for 4 sub-bands. Later, the statistical features were extracted from the biorthogonal wavelet 3 sub-bands of 30 subjects. In a similar attempt by (Yu et al., 2018) pre-processed data was collected from the SONY wellness tracker and telehealth monitoring device. The heart rate (HR) continuous measures, one-day period into six 4-hour time intervals segmented. For example, the interval ranges from 2pm-6pm, 6pm-10pm, 10pm-2am, 2am-6am, 6am-10am, and 10am-2pm. The variation of HR data within each time session was calculated and the predictor variables with the wellness, named (HR) _1 to (HR) _6 accordingly. Therefore, 'sleep' and 'step' data was aggregated into day-by-day epochs, otherwise referred to as total sleep duration (TSD) and a total number of steps (TSC). Nevertheless, the aggregation approach describes the elderly involved in overall daily lifestyles.

4.5 Feature Extraction

Feature extraction is the process of identifying the lower set of attributes or health parameters that can accurately diagnose and detect health issues. Identification of the best features for a health monitoring system is one of the critical phases in smartphone and wearable sensors data or images extraction and classification as the process helps to minimize detection errors and computation time (Nweke et al., 2019). The features could mean the normalization of mathematical metrics that generally capture the appearances of health parameters. Hence, we highlight different features extraction methods various authors implored for extracting data from the system for efficient implementation. Fig. 4(e) shows the feature extraction process.

Generally, feature extraction can be broadly categorised into convention feature and automatic feature representation. The two main feature extraction methods are explained below.

4.5.1 Conventional methods

In health monitoring systems, conventional features involve the use of hand-engineered features to develop efficient analyse of health data collected from sensors. The majority of the features include time domain and frequency domain-based features. Time-domain-based features include statistical parameters extracted from raw sensor data. Time-domain features provide low computation time and are applicable for online health monitoring systems. Typical examples of time-domain features include meaning, median, standard deviation, signal magnitude, percentile, root mean square, etc. On the other hand, the frequency domain feature helps to depict the distribution of energy in the signal. Frequency domain features are extensively utilized health monitoring domain especially in human activity recognition where they help to characterize repetitive activities. Examples of frequency domain features include Fast Fourier transform (FFT), discrete cosine transform, spectral energy, entropy, power spectral density, Fourier coefficient, and wavelet (Giorgi, Galli, & Narduzzi, 2020; Kumari & Rani, 2020; Nweke, Teh, Mujtaba, Alo, & Ali, 2019; Subasi et al., 2020). These conventional methods have been widely utilized for the implementation of the health monitoring system. For instance, Kumari & Rani, (2020) extracted medical images using five feature extraction approaches such as LBP, GLRM, CLBP, GLCM, and LTrP with the help of SVM and Multi-Layer Perceptron using Backpropagation Network (MLPBPN) for data analysis. GLCM uses co-occurrence or dependency matrices based on the gray level and distribution of pixels which measure the texture of the image. GLRM is based on the histogram of the image and LBP is a notably used approach for extracting features from computer vision images which requires simple calculations and invariance to illumination. Also, Nandy, Saha, & Chowdhury, (2020) extracted time and frequency domain features from sensor data to recognize various human activities such as sitting, walking, standing. The extracted features were fed to the Bayesian classifier, decision tree, k-NN, and SVM and implementation achieved 96% accuracy. More so, the time-domain waveform was utilized to extract features of smartphone-based IoT systems for personal health monitoring in a recent study by (Giorgi et al., 2020). However, conventional (handcrafted) based features are application dependents and cannot be transferred to similar health monitoring applications. In addition, it is time-consuming and difficult to model complex health data or support the dynamic nature of the current IoT databased data collection (Alo, Nweke, Teh, & Murtaza, 2020).

4.5.2 Automated methods

To resolve the issue in conventional feature methods for efficient health monitoring, recent studies have proposed automatic feature representation using deep learning methods (LeCun et al., 2015). The deep learning method utilize multiple layers of neural networks to automatically extract discriminant features from sensor data. Examples of deep learning models that have played important role in health monitoring and disease diagnosis applications include convolutional neural network (CNN), Generative adversarial networks (GAN), Deep Boltzmann machine (DBM), Deep Auto encoder, Restricted Boltzmann machine, Long short term memory and Gated recurrent unit (Nweke et al., 2019; Zhao et al., 2016). Some of the recent studies that utilize automatic feature representation for health monitoring are explained below. Automatic feature representation based on deep learning with a 3D CNN layer was deployed to extract features such as blood biomarkers, chronological age, and physical activity in order to predict the biological age at which someone was born (Rahman & Adjeroh, 2019). Also, shallow CNNs help to automatically extract more discriminative features of sensor input from human activity recognition (HAR) such as sitting, lying, walking, cycling, etc., deployed with Raspberry Pi 3 B plus for efficient human health monitoring (Huang, Zhang, Gao, Min, & He, 2021). A deep belief network (DBN) was combined with body sensors such as accelerometer and gyroscope to extract features for human activity recognition purposes, which was subjected to further analysis to reduce the dimensionality of features after removing noise and performing statistical analysis on sensor signals (Hassan, Huda, Uddin, Almogren, & Alrubaian, 2018). The analysis achieved overall accuracy of 97.5%.

A recent study by Qian et al., (2020) utilized deep neural network (DNN) architecture such as MLP and CNN to extract features on fall detection based on a wrist-worn device such as smartwatch and smartphone in regards to monitoring the users' daily activities and fall detection, which brings convenience to users. In another related study Loey, Smarandache, & Khalifa, (2020) implemented GAN and deep transfer learning (DTL) to extract check X-ray images for COVID-19 severity detection. Three DTL models such as the RESTNET18, ALEXNET, and GOOGLENET was selected and achieved an accuracy of 80.6%, 85.2%, and 99.9% respectively. Also, GAN utilized two neuron networks such as Auxiliary Classifier GAN (ACGAN) and Conditional GAN (CGAN) with data augmentation to improve COVID-19 detection which produced 95% accuracy (Waheed et al., 2020). In addition, the deep learning-based GAN architecture helps to extract chest radiograph images for effective detection of COVID-19 (Sakib, Tazrin, Fouda, Fadlullah, & Guizani, 2020). In a recent implementation, Conditional Partial-Residual Graph Convolutional Network (CPR-GCN) was utilized to extract 3D image features for effective automated anatomical labeling in coronary artery disease diagnosing procedures (Yang, Zhen, Chi, Zhang, & Hua, 2020). The proposed deep learning approach produces a 95.8% mean-Recall. In addition, GCN architecture has been deployed to diagnose multiple cardiac disorders from 12-lead ECGs (Jiang et al., 2020). In like manner, deep learning such as Descriptive Contractive Slab and Spike Convolutional Deep Boltzmann Machine (DCssCDBM) framework was proposed to extract EEG spectral images for early Alzheimer's disease diagnosis (Bi & Wang, 2019). Parkinson's Disease Diagnosis parameters were extracted from EEG Signals using the deep learning (e.g. CNN) model (Oh et al., 2020; X. Wang et al., 2020). Automatic feature representation using deep learning has become dominant implementation for health monitoring due to its ability to extract features from multiple sensors with minimal human intervention.

4.6 Data Analysis

This section focuses on the analysis of the extracted data. The extracted feature is converted to master feature vectors and fed to machine learning algorithms for health diagnosis and detection of ill-health as shown in Fig. 4(f). Various machine learning such as support vector machine (SVM), decision-tree (DT), k-nearest neighbor (k-NN), and Naïve Bayes (NB), etc. have been utilized by various studies to analyze health-related data (Nedungadi et al., 2018). For instance, an earlier study by Jin et al., (2014) analyzed features extracted from sensor data using a support vector machine (SVM) classification model to determine the severe health status of chronic obstructive lung disease. In another related study by Enamamu et al., (2020) extracted data from each member of deviation and then carryout training with the data using a Neural network (NN). The statistical package and MATLAB were also utilized for both analysis and simulation to obtain the mean absolute error (MAE) of an acceptable value of 1.39BPM. The analyzed data is viewed in the web interface for decision-support in the healthcare delivery centre. Also, visualization techniques were deployed to analyze data obtained from the sports exercise (Mora et al., 2017) and different cardiac detection algorithms such as ST-segment, T-wave, RR interval abnormality detection of ECG, and features derivation of Seismocardiography (SCG) to detect patients in critical health situation (Sahoo et al., 2017). Likewise, a recent study by Subasi et al., (2020) analyzed the pre-processed data using machine learning algorithms such as k-NN, Decision-tree (DT), ANN, etc. to reduce attributes used to assess biomedical signals of patients with life-threatening diseases. Conversely, in the healthcare monitoring of the elderly, the data was extracted and analyzed using combination of machine learning and statistical methods such as ANN, SVM, Decision-tree, and LASSO regression for classification and prediction of fall and energy expended during intensive exercise. Furthermore, in a different manner, (Santhi et al., 2017; Syed et al., 2019) attempted to analyze features using big data analytics technologies such as Mahout and MapReduce frameworks that split the data into distributed format, data mapping, shuffling, and classification. Mahout extends the machine learning library such as multinomial Naïve Bayes algorithms to analyze and determine the physical activities level of each subjects.

4.7 Evaluation Measure

In this section, we present various system evaluation measures deployed by various authors in achieving their set aim, and objectives of each proposed system or model for the health monitoring systems. Fig. 4 (g) depicts various evaluation measures utilized by recent studies in heath monitoring. After extensive review, we chose to elucidate important evaluation measures such as accuracy, confusion matrix, sensitivity, recall, specificity, precision, F1-score, computational time, and other likelihood measures such as mean absolute error, error rate, system usability scale (SUS), etc. nonetheless, accuracy is the ratio of the correctly labeled subjects to the entire pool of subjects (Ikegwu, Nweke, Alo, et al., 2021; Kumar et al., 2018). Specificity means correctly negative label by the system to all who are healthy in realism (Yu et al., 2018). Sensitivity concentrated on a test to correctly identify those with the subjects (true positive rate) (Sahoo et al., 2017). Recall expresses the ability of the classification model to reflect all appropriate instances (Syed et al., 2019). Precision also has the ability of the classification model to return all necessary instances (Subasi et al., 2020). F1-score is interested in the combination of precision and recall with the introduction of the harmonic mean (Verma et al., 2017). The receiver operating characteristic (ROC) curve is in form of plots that express the true positive rate (TPR) and the false positive rate (FPR) as a function of the model's threshold for classifying a positive (Subasi et al., 2020). The area under the curve (AUC) describes a metric to calculate the overall performance of a classification model based on the area under the ROC curve (Subasi et al., 2020). We also, comprehensively present the evaluation measures of different works developed to guide all intended system analysts, developers, researchers who are interested in building efficient systems to stand the taste of the time in the healthcare monitoring system in the contemporary healthcare delivery services. For instance, Kumar et al., (2018) evaluated the disease prediction and diagnosis system for healthcare using accuracy, specificity, and sensitivity with four classifier such as k-NN, NB, DT, and SVM methods.

In addition, a study by Verma et al., (2017) evaluated the proposed model with four performance matrices such as accuracy, sensitivity, f-measures, and specificity using different classifier techniques such as k-NN, NB, SVM, DT, and ANN. Also, cardiac early warning system with only two performance measures such as accuracy and true positive rate (TPR) using ECG and SCG parameter, where Accuracy measures the overall performance of the algorithms, and TPR is the performance ability of the algorithms (Sahoo et al., 2017). An earlier study by (Juen et al., 2014) obtained an accuracy of 94.13% during walk distance measurement using linear regression of gait model. Also, mean absolute error (MAE) was used to evaluate the heart rate (HR) tracking during physical exercise using PPG signals which 1.39BPM was achieved (Essalat et al., 2016). Another similar study evaluated the proposed commercial pedometers with average counted steps, standard deviation, and error percentage (Beevi et al., S2016). To this effect, another study by Mora et al., (2017) evaluated a proposed framework with a single performance matrix that is sensitive using sports athletes' position parameters such as name, age, time played, maximum speed, and distance covered.

More so, other authors attempted to use a different approach for evaluation, for example, systems usability scale (SUS) and questionnaire with five users containing gender and age parameter to evaluate the proposed IoT wearable device for health monitoring of older people (Dur et al., 2019; Junde Li et al., 2019). The work by Abdulghaffar et al., (2019) evaluated the proposed system with throughput in terms of total packets received in a time interval. Update time intervals incorporate a tuneable parameter that is adjustable by any authorized user and determine the possibility of receiving data frequently from patients. Similarly, Al-khafajiy et al., (2019) evaluated the proposed system architecture of wearable sensors with a prototype in terms of efficiency and scalability. Another system architecture was evaluated with a fog layer using latency and CPU usage (Debauche et al., 2019; Kharel, Reda, & Shin, 2017). Also, day-wise average and standard deviations compute parameter latency using SMS and Web data parameter for evaluation (Swaroop et al., 2019). Furthermore, recently, several studies have utilised performance metrics to evaluate different aspects of health monitoring system development and implementation and it proved effective. For instance, Yu et al., (2018) evaluated the proposed model with a confusion matrix having five performance measures as Accuracy, Precision, Recall, Specificity, and F-score. In a different measure, the filtration technique was implored to evaluate an energy-efficient model for wearable sensors signal using three-parameter such as a notch, low-pass, and high-pass filters. By utilizing the performance matrix, several proposed models can be realised and tested. In a bid of that, (Syed et al., 2019) applied the technique to evaluate the proposed system with two measures Precision and Recall to predict physical activities such as cycling, climbing, jogging, standing, running, walking, etc. based on confusion matrix. In another manner, a deep learning approach such as a recurrent neural network was utilised to evaluate the system using the participant variable such as age, weight, and height where daily life movement samples of 112 and 96 fall samples were (Taramasco et al., 2018). Another related study by Liu & Li, (2018) evaluated the system with clustering k-anonymity, which concentrates on security focuses on parameters such as height, weight, age, and sensitive data collected by the tri-axis accelerator sensors from the analysis. However, the sensitive data of all the data extracted remains invariant. In the same order, (Subasi et al., 2020) implored k-fond cross-validation techniques in case of running out of samples to evaluate the proposed model. The authors automatically split the available dataset into k-subsets randomly and performed iteration on the subsets, thereby virtualizing the training and validation. Also, measure accuracy, precision, recall, f-measures, receiver operating characteristic (ROC) area, and Kappa value. Another contribution by Thaung et al., (2020) attempted to evaluate the system through visualization with ThingSpeak using correlation matrix of human activities parameter such as sitting, running, walking, standing, climbing. Another attempt by Enamamu et al., (2020) evaluated the proposed model with classification method to compute EER (equal error rate), FAR (false acceptance rate), and FRR (false rejection rate). Hence, the output comes in form of TN-true negative (0), TP-true positive (1), where TN represents non-patient information (NPI) while TP represents right-patient information (RPI).

Table *4* shows various health monitoring system evaluation measures, formulae and description.

Table 4. Health monitoring evaluation measure, formula, and description.

Evaluation measure	**Formula**	**Description**	**References**
Accuracy	$\frac{(TN+TP)}{(TN+TP+FN+FP)}$	This is the percentage of time the system order was created correctly. Where TP=true positive, TN=true negative, FP=false positive, FN=false negative	(Kumar et al., 2018; Sahoo et al., 2017; Subasi et al., 2020; Verma et al., 2017; Yu et al., 2018)
Sensitivity	$\frac{TP}{(TP+FN)}$	Focuses on a test to correctly identify those with the disease (true positive rate)	(Kumar et al., 2018; Sahoo et al., 2017; Verma et al., 2017)
Specificity	$\frac{TN}{(TN+FP)}$	Percentage of correctly predicted better system order to the total number of better system orders from the dataset instances	(Kumar et al., 2018; Verma et al., 2017; Yu et al., 2018)
Precision	$\frac{TP}{(TP+FP)}$	The ratio of instance, classified as a number of positive in all instances.	(Subasi et al., 2020; Syed et al., 2019; Yu et al., 2018)
Recall	$\frac{TP}{(TP+FN)}$	This is classified as a true positive rate	(Syed et al., 2019; Yu et al., 2018)
F1-score	$2x\frac{precision\ x\ recall}{precision\ +\ recall}$	Harmonize mean between precision and recall	(Subasi et al., 2020; Verma et al., 2017; Yu et al., 2018)
Confusion matrix	*Combine two or more evaluation or classification model*	This is a table that shows the performance of a classification classifier for which set of test data whose true values are known	*X*
Error rate (ERR %)	$\frac{ES-CS}{ES}\ x\ 100$	ES = number of expected steps, CS= average number of counted steps. Thus ERR = error in percentage.	(Beevi et al., 2016; Enamamu et al., 2020)
Mean absolute error (MAE)	$\frac{\sum_{i=1}^{n}\lvert y_i - x_i\rvert}{n} = \frac{(\sum_{i=1}^{n}\lvert e_i\rvert\ )}{n}$	$\lvert e_i\rvert = \lvert y_i - x_i\rvert$ = is arithmetic average of the absolute errors, y_i = prediction, x_i = represent the true value	(Essalat et al., 2016; Juen et al., 2014; Swaroop et al., 2019)
System usability scale (SUS)	*x*	Shows quick and dirty reliable tool for measuring the *usability*. Normally consist of questionnaire from Strongly agree to Strongly disagree	(Dur et al., 2019; Junde Li et al., 2019; Yavuz, 2019)
Receiver operating characteristic (ROC) area	*x*	Allows classifier performance evaluation on multiple operating points	(Subasi et al., 2020)
Kappa value	*x*	This is expected value by calculating the predictor's successes based on the area under the ROC curve	(Subasi et al., 2020)

Evaluation measure	Formula	Description	References
Computational time	x	Maintain time interval and cycle	(Abdulghaffar et al., 2019; Al-khafajiy et al., 2019)

5. Domains of Mobile and Wearable Sensors for Health Monitoring System

Wearable devices and their enabling sensors have changed the perception of our daily computing from traditional methods to digitalized means. It increases the computing efficiency in our market enterprise. The typical application area where mobile and wearable devices are mainly developed is shown in Fig. 5, while a brief analysis of these application areas is provided in Table 5.

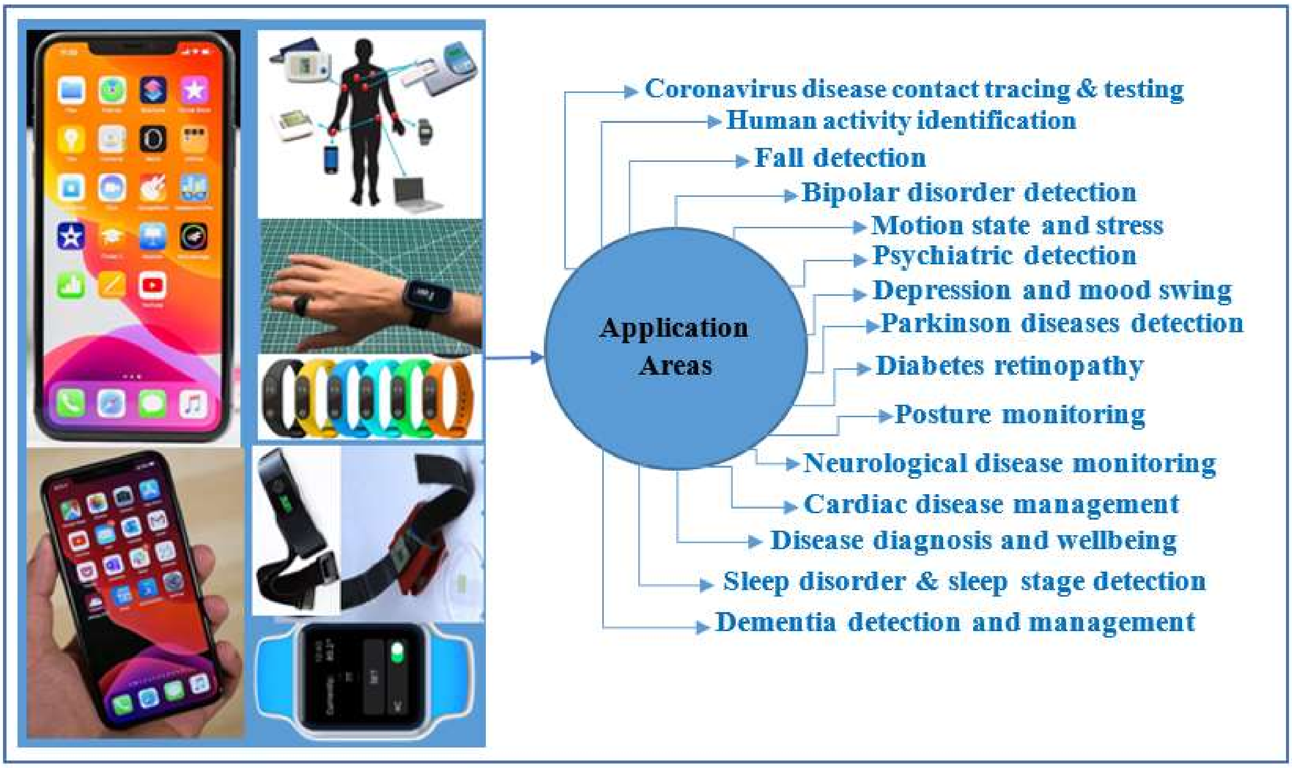

Fig. 5. The typical application areas.

Major studies in mobile and wearable sensors for health monitoring systems are implemented for coronavirus disease contact tracing and testing, human activity identification, sleep disorder, and sleep stage detection, fall detection, bipolar disorder detection or social anxiety, motion state, and stress detection, psychiatric detection, and depression and mood swing (Saeb et al., 2015). Other important applications of sensor-based health monitoring systems include Parkinson diseases detection, cardiac disease management (cardiovascular), disease diagnosis and wellbeing, neurological disease monitoring, diabetes retinopathy, posture monitoring, and dementia detection and management (Acton, Elsaleh, Hassanpour, & Ahrabian, 2018). These applications are discussed in the following subsection.

(i) Coronavirus disease contact tracing and testing

Coronavirus disease is otherwise known as COVID-19 (Alo et al., 2022) is a novel virus from a virus family that is causing serious illness and threatening human life existence and could lead to untimely death. COVID-19 has become a global issue recently, where over 200 countries have been threatened and are crumbling leading to economic downturns. The symptom of the novel COVID-19 includes respiratory disease characterized by cough, body temperature (°C), sputum production, fever, dizziness weakness, pneumonia, dyspnea, etc. World Health Organization (W.H.O) announced the fast-spreading coronavirus outbreak as a pandemic on March 11, 2020 (Sun et al., 2020). Presently, as of July 16, 2021, W.H.O has reported over 189.8 Million confirmed COVID-19 cases, 173.2 Million recoveries, over 4 Million reported deaths, and over 3 Billion vaccines have been administered. To date, a lot of research is ongoing to discover either drug for effective treatment or vaccine, however, there is no drug, herbal medicine, or vaccine that has proved effective or been clinically accepted worldwide (Sun et al., 2020). Nonetheless, many people are still getting infected and tested every day. Although, some measures have been adopted and enforced to prevent the spread of the virus, and ease pressure on the medical care system. The measures to curtail this novel virus excavating and ravaging the world human health include total lockdown, wearing of a nose mask, observing social distancing, etc., especially to enable the medical health workers and other agencies such as task force committee setup and security personnel to embark on quick contact tracing and testing. However, to combat require smart technological devices such as smartphones. Existing techniques such as clinical analysis of chest CT scan images and blood test results are widely used but these techniques require high-tech installation, time-consuming process, and the cost of acquiring them is high. Hence, smartphones are needed to speed up the processes. From our extensive review, only 4 out of 85 primary papers selected discussed the coronavirus-19 pandemic contact tracing and testing. These studies include (Aminian, Safari, & Razeghian-jahromi, 2020; Maghdid, Ghafoor, Sadiq, Curran, & Rabie, 2020; Schuller et al., 2020; Sun et al., 2020). These studies are explained below.

Maghdid, Ghafoor, Sadiq, Curran, & Rabie, (2020) proposed a smartphone-enabled sensors framework such as cameras, microphones, temperature sensors, inertial sensors, proximity, color-sensor, humidity-sensor, and wireless chipsets to detect coronavirus disease through contact tracing and testing. The integrated framework system has quality and qualified features such as low-cost solutions, portable, and high-accuracy recording, as well as offer self-help. In addition, the presence of artificial intelligence (AI) in the proposed framework helps to predict the result after testing with the smartphone. Furthermore, smartphones are now playing a smart and vital role in the fight against the COVID-19 pandemic. For instance, it is used in telemedicine and virtual visits for perioperative visits, bulk short message system (SMS), and reduce the risk of spreading the infectious diseases during outbreaks and after the disease treatment (Aminian et al., 2020), behavioural changes can be monitored from the suspected and confirmed COVID-19 patients in the treating or isolation centre (Sun et al., 2020), and speech and sound analysis for coronavirus crises (Schuller et al., 2020), and COVID -19 data can be analysed to aid prediction and future occurrence forecast (Ikegwu, Nweke, Anikwe, Alo, & Okonkwo, 2021).

(ii) Human Activity Identification

Over the years, the mobile health monitoring system has been widely utilized in human activity identification. The human activity involves daily life exercises and actions such as hamstring exercises (Hegyi et al., 2019), maximal voluntary contraction (Michelsen et al., 2020), muscle contraction (Lim et al., 2020), walking-age patterns (Jin et al., 2014), and elderly physical activities (Syed et al., 2019), etc. Effective monitoring of human activities in the young and elderly helps to improve the rehabilitation, lifespan, sports, and early detection of musculoskeletal diseases and the general wellbeing of an individual. It has been informed that an individual's walking patterns are related to some of their health conditions (Jin et al., 2014; Juen et al., 2014; Lee et al., 2014). Recently, various research efforts have been conducted in the human activity application area either in detection or monitoring with some dual or heterogeneous sensors (Thaung et al., 2020). From the primary studies, we identified 7 out of 85 recent primary studies that applied smartphone and wearable sensors for human activity identification. Although this area has attracted wide research interest (Nweke, Wah, Al-garadi, & Alo, 2018; Nweke et al., 2019; Zhao et al., 2016) we analysed recent human activity recognition using mobile and wearable sensors. The research implementation in human activity has led to early detection and monitoring of health circumstances surrounding the daily life and ambient assisted living (AAL) of an individual. For instance, Spinsante et al., (2016) highlighted the problem of long sitting times in the workplace, which they implemented a mobile health-based system to test and monitor the sitting positions in the organizational workplace. Therefore, six activities were considered, hence, 99% accuracy was achieved with regards to sitting (not active) and active states. In addition, patients with some health conditions such as diabetes, hypertension, obesity, and heartburn due to smoke are often subjected to perform well-defined physical training as a part of their treatment. For example, a recent study by Syed et al., (2019) implemented a smart healthcare platform interconnected with sensors through IoMT and machine learning algorithms to analyse and make a quick treatment recommendation. The platform successfully predicted twelve (12) physical activities in elderly people especially those with critical health conditions, hence, 97.1% accuracy was obtained. Other aspects, mobile health monitoring systems have recorded an impressive result in the area of human activities include step count using slow walking speed (Beevi et al., 2016), concurrent activities (Chen & Wang, 2017; Sodhro et al., 2018), ambulatory (Sundaravadivel et al., 2017), and weight sensing (Lim et al., 2020).

(iii) Sleep disorder and sleep stage detection

Interestingly, sleep plays a key role in the healthy living of the human race and guards against mental and physical ailments. Sleep is said to be general recurring physiological activity. However, lack of quality sleep affects human health, which can result in sleep disorders or diseases such as insomnia and obstructive sleep apnea that might advance to daytime sleepiness, irritability, depression, anxious mood, and eventually may lead to death (Zhang & Wu, 2017). Insufficient sleep is a public health challenge and needs serious attention. Therefore, effective diagnosis and treatment of patients with sleep-related disorders is currently an urgent and important research area in the mobile health monitoring system. Hence, out of 85 primary studies selected, only 4 of the studies discuss in-depth how sleep disorder and stage detection were implemented using smartphones and wearable sensors technology. For instance, Robbins et al., (2018) examined the deployment of smartphones for sleep tracking in a developed country such as the USA using variables such as cigarette smoking, physical activity, self-reported health, diet, and disease diagnosis as the base factor. However, the result shows that sleep tracking is more effective for those with good general health. Furthermore, in order to address sleep disorder, an IoMT cloud-based real-time framework was developed for the detection of sleep apnea using SpO_2 estimation (Haoyu, Jianxing, Arunkumar, Hussein, & Jaber, 2018). Another similar study by Dey et al., (2017) developed wearable smartwatches enabled with PPG sensor for continuous daily alertness tallies such as awake, long sleep, and short duration power snap. Hence, the system achieved an accuracy of 80.1%, which offered better sleep management of health. Also, heartbeat interval estimation during sleep is detected (Br, 2014) to improve the sleep stage.

(iv) Fall Detection

Fall constitutes the foremost cause of injury, disability, and possibly death in individuals especially the elderly or aged people. There are several approaches deployed for fall detection such as device-based which senses the accelerations, ambient sensor-based that make use of vibrational data, and vision-based which uses the camera. However, it requires more universal device detection through available technology such as smartphones, and heterogeneous sensor (Evangeline, 2018; Hakim et al., 2017). Smartphone built-in with accelerometer sensor technology has been widely utilized in the fall detection area of the health monitoring system. In recent years, there has been an increasing interest in classifying and detecting fall events in most scenarios using smartphones with multi-sensors such as accelerometers, gyroscopes, and magnetometers (Giuberti et al., 2015). Moreover, the primary studies (Giuberti et al., 2015; Hakim et al., 2017; Lee et al., 2014; Lee et al., 2018) out of 85 selected studies were implemented for fall detection.

For instance, Lee et al., (2018) utilized smartphone to classify and detect fall in daily life such as walking, running, sitting, and falling using enabled Google's 3D mapping services to provide the tracking location. This achieved high accuracy and speed, thereby assisting in providing solutions to fall-related problems. In addition, motion artifacts in wearable ECG device were reduced while monitoring and detecting fall during routine exercises such as standing and walking at 7km/h speeds (Lee et al., 2014).

(v) Bipolar disorder detection or social anxiety

Bipolar disorder (Abdullah et al., 2016; Gr et al., 2014) is a mental related illness. Some common transition signs experienced by patients affected by bipolar disorders (BD) include more common successions of periods of a manic, normal, and depressive state, though, mostly resulting in conflicts in rhythmicity. Presently, there is no cure for bipolar disorder, though, pharmacotherapy can be adopted to help the (Abdullah et al., 2016). However, the earlier study by (Gr et al., 2014) is much more concerned with the use of technology for early detection of BD health conditions or social anxiety created as a result of mental health problems. The researchers implemented smartphone-based technology to detect social anxiety in bipolar disorder. Recently, numerous researches have been carried out in order to detect social anxiety using smartphone technology. For instance, Huang et al., (2017) implement a non-invasive mobile sensing phone application to examine the social anxiety of students (no) in the college using GPS track location. However, social anxiety may result due to students' visited and location transitions. The mobile applications were deployed and recorded higher accuracy in the detection of social anxiety disorders.

(vi) Motion state and stress detection

Motion state and stress-related issues are affecting the physiological characteristics of human health. Motion state and stress (Zhou, 2020) refers to human physiology, mental stability, and unstable state which might result in a degree of misjudgment. It affects the state of the mind, especially when carrying out an exercise or when one receives shocking information. The utilization of biosensors technology to monitor and detect the human state of change parameter in real-time to assist in the prevention, diagnosis, and treatment of diseases is very important. The biosensor such as ECG and EEG are mostly integrated with smartphones to record the physiological signals. Smartphone technology implementation in the healthcare sector has played a vital role in motion state and stress detection. Various research efforts have gained momentum in using the phone to detect the change in motion and stress management. From the review carried out, out of 85 primary papers, only 2 papers implemented a system for motion state detection. For instance, Wannenburg & Malekian, (2015) implored a smartphone system to monitor the medical stress of patients after being discharged from the hospital. The system is integrated with heterogeneous sensors to monitor and measure accurate information, offer feedback, and communicate with the medical healthcare provider thereby reducing medical stress. Furthermore, the physiological signal acquired from heterogeneous sensors was analysed and classified in order to solve the issues of individual's cognitive-affect mental states, which has become a growing challenge facing the brain-computer interface (BCI) scholars (Xu & Plataniotis, 2016).

(vii) Psychiatric detection

Psychiatric is a mental health disorder that affects the state of the mind and brain thinking faculty. Psychiatric disorder (Difrancesco et al., 2016) if not detected and treated on time might lead to a complex mental illness called Schizophrenia. Schizophrenia is characterized by hallucinations, delusions, and chaotic thinking. The early intervention to assess, identify and detect warning signs from critical mental illness due to mental health changes in an individual requires smart healthcare technology such as smartphones, sensors, and communication devices. To address this health challenge that deepens the mind of our community health provider. Numerous studies have been carried out by different researchers. From the thoroughly analysed implemented research papers, 3 primary papers (Ben-zeev et al., 2015; Difrancesco et al., 2016; Wang et al., 2016) reviewed were utilized for psychiatric detection. First of all, Ben-zeev et al., (2015) examined the level of smartphone usage in tracking and detecting mental health challenges. Hence, a smartphone built-in with sensors technology such as accelerometer, ambient light, GPS, etc., detect depression, stress, and subjective loneliness over time with a highly accurate level, however, it requires an improvement to tackle several mental health behavioural indicators. Furthermore, the data generated from smartphones were great of importance especially when modeling and developing an intervention approach to address the psychiatric disorder. The study shows that smartphones predict changes in the mental health of outpatients with schizophrenia up to 7.6% mean error of the average score (Difrancesco et al., 2016; R. Wang et al., 2016).

(viii) Depression and mood swing monitoring

It is becoming a global concern, the negative economic impact created as a result of depressive major disorder (MDD) is not only affecting the economy but also the social circle and individual’s mental health. Some of the recent studies that evaluated depression and mood swing monitoring are discussed below. Depression and mood swing (Saeb et al., 2015) involves mental health disorder. MDD has a common disease such as impaired daily functioning and worsening of co-morbid medical illness. Mood disorders are further known because symptoms overlap with cognitive and motor features of Parkinson's disease (Ray & Agarwal, 2019). The only common solution to depression and mood swings is applying antidepressants and psychotherapy methods; nonetheless, the question remains, “how many people can access this treatment approach mechanism”. Therefore, there is a need to deploy smartphones to detect depression and mood swings timely for human health monitoring and treatment. In this aspect, a lot of research effort has been made to provide better remote, real-time analysis and approaches in diagnosing and treating such individuals through a technologically smart approach. For instance, Asselbergs et al., (2016) implemented smartphone usage logs for modest ecological momentary assessment such as diaries, questionnaires, self-mobile generated questions and answer the same at prompted time points to expose the depressive mood. However, monitoring proxies of mental health which include theoretical variables such as physiological states, social interactions, and social environments. Also, analysing the mobility patterns from GPS traces (Canzian & Musolesi, 2015) and utilization of machine learning techniques to predict antidepressant treatment response (ATR) up to 88% accuracy helps to monitor depressive patients (Alo, Ele, & Nweke, 2019; Jaworska et al., 2019).

(ix) Parkinson’s disease detection

Parkinson’s disease (Poewe et al., 2017; Ray & Agarwal, 2019) is one of the most neurodegenerative disorders that affect mostly the aged people between 65years and above.

From the extensive review, 5 primary studies out of 85 implemented research papers utilized mobile and wearable technology for addressing the inherent issues with Parkinson's diseases. Therefore, Parkinson’s disease (PD) is related to many non-motor symptoms that complement to overall disability. Conventionally, it is characterized by motor symptoms such as bradykinesia, tremor, and altered gait, hence, dopaminergic neurons in substantia nigra might be lost. Nevertheless, there are some recommended drugs for the treatment of PD including dopaminergic drugs in terms of L-dopa. Over time, however, the effects of the drug can result in motor fluctuations that might lead to dyskinesia and involuntary movements. Nonetheless, presently, the measurement and detection of Parkinson's disease are subjective and subjected to clinical assessments, hence, by using this approach; the clinical trial will impose false positives or negatives, time-consuming, and cost-ineffective. To address this impressive problem, many research effort has been made to utilize smartphone technology to detect Parkinson's disease at an early stage. For instance, Zhan et al., (2018) implemented mPDS (mobile Parkinson disease score) mechanism to measure, test, and detect PD severity and evaluate the symptoms outcome with the standard measure, then respond to dopaminergic therapy. The mPDS system utilized 6148 smartphone activity assessments from 129 individuals, therefore, it improved the traditional clinical and therapeutics method in real-world assessments. Other aspects where the use of mobile phone technology enhances the Parkinson's diseases treatment include Parkinson disease management (Trister, Dorsey, & Friend, 2016) and kinematic analysis and evaluation using leg agility of sit-to-stand linking UPDRS (Unified Parkinson’s disease rating scale) score (Giuberti et al., 2015).

(x) Cardiac disease management (cardiovascular)

Mobile phones with enabled sensors technology have played a vital role in this contemporary era in monitoring and managing cardiac disease patients. Cardiac disease management entails the different aspects of diagnosis, testing, and total care using various strategies, approaches, measures, and techniques implemented to address the inherent nature of cardiac diseases such as heart failure, hypertension, high blood pressure, heart rate, and pulse rate, etc. majority of the studies reviewed were carried for cardiac disease management. Cardiac disease (Iftikhar et al., 2018; Neyja et al., 2017) is a killer disease associated with the heart or blood vessel or simply means disease of the heart. The examples of some cardiovascular diseases (CVD) include myocarditis i.e. inflammation of the heart muscular part, arrhythmia (heart rhythm irregularities), cardiomyopathy (muscle disease and heart malformations occur at birth), vascular (diseases related to arteries, lymph vessels, and veins), and stroke (short blood flow to the brain level), etc. (Badar et al., 2020; Du, 2016). Several techniques such as ECG, echocardiography has been deployed to detect CVD such as atrial fibrillation, heart failure, myocardial infarction disorders, etc. however, it is difficult to operate and much costly, hence, smartphones are preferred or implemented to either improve or enhance the existing methods because of its effective monitoring and analysis of cardiac-related patients before or after operations to minimize the risk of hitches, and offer self-monitoring (Bánhalmi et al., 2018). Recently, more research effort has been intensified to leverage the use of a smartphone to classify and manage cardiac disease patients. For instance, Elgendi et al., 2018; Mena et al., (2018) used a smartphone to collect and analyse the ECG signals using a machine learning approach for the treatment of arrhythmias disease in the elderly. This achieved high accuracy of 97%. More so, arrhythmias disease detected using smartphones recorded overall detection accuracy of 99.90% (Elgendi et al., 2018). Another area of cardiac disease management was noted in cardiac rehabilitation (Etiwy et al., 2019; Nair et al., 2018), cyanotic heart disease detection (Harris et al., 2019), heart rate disorder (Bánhalmi et al., 2018; Essalat et al., 2016), respiratory diseases (Maghdid et al., 2020; Wannenburg et al., 2018), heart rhythm (Poplas & Stani, 2016), breath disorder (Nam et al., 2016; Stafford et al., 2016), heart disease diagnosis

(Deshpande & Kulkarni, 2017), alertness scoring of heart rate for sleep or awake with an accuracy of 80.1% which offer better cardiac management (Dey et al., 2017), and early warning and monitoring mechanism for cardiac disease management (Kakria et al., 2015; Sahoo et al., 2017).

(xi) Disease diagnosis and wellbeing

Diagnosing and monitoring diseases and the general wellbeing of individuals periodically is very important even when you are not sick or ill. Applying proactive measures to check your body system health status against undeveloped disease or disease at the host system level awaiting for the maturity time or incubation period to mature is necessary because it can save cost and life, ensuring longevity and, reducing untimely death occurrence. Disease diagnosis and wellbeing (Nedungadi et al., 2018; Yu et al., 2018) involves the act of detecting, checkmating, carrying out the early diagnosis, getting acquainted with technological devices and methods that can effectively monitor the well-being of an individual, right health tips information sharing, and awareness creation. Some diseases could be managed with local medicines or less expensive drugs when detected on time but if allowed to fully develop could lead to medical escalations and most at times cause fatalities or death due to insufficient knowledge of embracing diagnosis mechanism (Abdulghaffar et al., 2019). For example, the new novel coronavirus diseases, when diagnosed on time, will prompt early treatment thereby saving life at its peak. However, most affected or confirmed cases that later led to fatality or death are detected late when the virus must have weakened the immune system. Various researchers have proposed or implemented different approaches to diagnose and monitor patients and mental health people, detection of early diseases at the host level, offer better strategy, foster and predict better healthy living. Some of these studies that concentrated on disease diagnosis and general wellbeing are discussed below. Recently, the application of information and communication technology and integrated computing systems such as the internet of things (IoT) and the internet of medical things (IoMT) enabled objects and people's virtual environment, the computing world, the information era, and the physical world to interact together. This interconnects devices paradigm led to prompt smart and healthcare delivery systems. For instance, Verma et al., (2017) implemented mobile-healthcare (m-healthcare) applications based on the internet of things that have multi-dimensional features to ensure the effective diagnosis of disease. The system offer prediction, regular health update, and healthy lifestyle information tips to millions of people thereby restoring the hope of better healthy living for everyone. Hence, it achieved an accuracy of 87.4 %. Also, a similar study by Swaroop et al., (2019) utilise the internet of things interconnected with a mobile device or web platform to monitor the vital signs such as blood pressure, heart rate, and body temperature of an individual and communicate to the healthcare system provider or doctors. The user gain more confidence psychologically because there is regular check-up and flow of health parameter information between the clinicians and the patient. In addition, fog internet of things was also designed to monitor the elderly patients severity which is effective in check-up by medical health workers who are designated to follow up with patients (Debauche et al., 2019), and the health safety of an individual was maintained using IoT enabled with smartphone built-in sensors (Wu et al., 2019). Moreover, mobile application based IoT technology was greatly utilized for health monitoring of total well-being of the elderly people (Al-khafajiy et al., 2019; Dur et al., 2019) and pregnant ladies (Santhi et al., 2017) use the sensors to generate physiological parameters such as heart rate, body temperature, and blood oxygenation to achieve optimum mental health. Furthermore, the m-healthcare application is widely utilized in diagnosing and monitoring different diseases such as myopathies (muscle tissue disease) (Sener et al., 2019), enhance blood pressure estimation and real-time blood pressure monitoring

(Simjanoska et al., 2018; Wang et al., 2018), and assess the pulse and oxygen saturation level present in the healthy teeth (Janani et al., 2020).

(xii) Neurological disease monitoring

Neurological disease (Gong et al., 2016) involves varied groups of disorders that are associated with progressive degeneration in terms of structure and function of the central nervous system. After critical analysis of the primary papers implemented in view to address the problem of neurological disease monitoring, seven (7) out of 85 papers was utilized in this subject area. Neurological disease is a mind destabilizing illness that needs proper monitoring. The common example of neurodegenerative diseases includes epilepsy (Subasi et al., 2020) and sclerosis (Kuusik et al., 2018), Parkinson's disease (Poewe et al., 2017), and other cerebrovascular diseases such as stroke, migraine, and brain tumors. These diseases affect the brain system thereby causing havoc to the activities of daily living (ADL), nevertheless, it can be effectively monitored using some technological mechanism such as a smartphone with enabled sensors technology. For instance, Subasi et al., (2020) implemented smartphone built-in sensors such as ECG and EEG to monitor epileptic seizure patients and other brain disorders such as brain tumor, stroke, and acute migraine. The system is practical, precise, and effective oriented in monitoring and analysing the biomedical signals to reduce the neurological disease health risk. Also, multiple sclerosis patients at home were diagnosed and monitored through sensor technology (Gong et al., 2016; Kuusik et al., 2018).

(xiii) Diabetes retinopathy

Over the years, diabetes has become an epidemic affecting over 422 million people in the world, posing a serious health challenge to so many countries (Jie Li et al., 2019). Various researchers are seriously working on different mechanisms or approaches to address this regenerated health concern. This, however, observed from 4 out of 85 implemented papers utilized mobile and wearable sensors for diabetic retinopathy diagnosis and monitoring. Though, as at present, the affected diabetic patients successfully manage to live all through one's daily life, as such has caused global concern. In addition, diabetic patients are associated with clinical manifestations of metabolic syndromes, such as hypertension, dyslipidemia, and obesity, which affect organs and body systems such as the heart, blood vessels, eyes, kidneys, nervous system, etc. Nevertheless, diabetic patients need to be diagnosed and monitored just like any other patients suffering other diseases such as Parkinson's and neuropathy, hence, there is a need for a technological-driven approach such as smartphones, the internet of things, etc. Various researchers are seriously working on different mechanisms or approaches to address this regenerated health concern. For instance, Sharma, Subramaniam, Lakshmikanthan, Krishna, & Sundaramoorthy, (2016) developed a smartphone having a fundus camera device to detect diabetic retinopathy mid-peripheral fundus in grade II cataracts. Also, mobile phone applications integrated with the internet of things were greatly utilized in diagnosing and monitoring of diabetic patients, which maintain a cordial interaction between the patients and the physicians or doctors (Chhiba, 2019; Kumar et al., 2018).

(xiv) Posture monitoring

Posture monitoring involves a different aspect of the body position. When the position of the body or sitting posture is badly placed, it can cause pains and decrease the flexibility of the joints making it prone to injuries. For example, over 80% of individuals are experiencing pains in different parts of the body such as the back, waist, neck, lower and upper abdomen, etc., however, if it is not monitored and treated on time may lead to extreme hunched back (hyper-kyphosis) (Acharya et al., 2019). Therefore, apart from the medical attention, and physiotherapist's approaches, it requires more technological measures to effectively monitor the patients even while at home. With regards to this development, much research work has been done to address these health issues facing humans. For instance, Roh et al., (2018) implemented a system using sensors technology and machine learning algorithms to classify and measure up to six sitting postures such as upright sitting with backrest, front sitting with backrest, left sitting, and right sitting, etc. The algorithms achieve classification rates of 97.20% and 97.94% from the actual sitting posture and achieve high posture-estimation accuracy thereby reducing the body pain as a result of bad postures. Also, various postures were monitored to reduce back and neck pain using the ATmega328 phone (Acharya et al., 2019; Nweke, Teh, Al-garadi, & Alo, 2018).

(xv) Dementia Detection and Managements

Emerging technology is targeted at detecting and managing dementia in their daily lives. For example, one of the health implications of dementia is that it causes Alzheimer's disease that varies in dealing with early symptoms based on individual systems (Ishii, Kimino, Aljehani, Ohe, & Inoue, 2016). Alzheimer's disease is a progressive disorder that degenerates (left brain cell empty) and dies. Therefore, dementia (Acton et al., 2018) is referred to as a syndrome that is characterised by symptoms associated with progressive brain dysfunction and total impairment of cognition. Dementia is accompanied by loss of memory, thinking faculty, comprehension, judgment and emotion, and other hidden symptoms, thereby losing activities of daily living (ADL) functionality. Presently, in the world, today over 46.8 million people are experiencing dementia and expected to increase to 74.7 million by 2030, and even 131.5 million by 2050 which has affected and threatened quality of life as well as exhibiting independent live (Acton et al., 2018). Although, dementia mostly occurs in elderly people. Several studies have been carried out for early symptom detection and better means of managing those living with dementia in our society today. With regards to this, smart driven technology devices and sensors have been widely utilized for dementia health disorders. From the in-depth review, we discovered that 7 primary studies from 85 selected studies were implemented to solve dementia-related issues using smartphones and wearable technological mechanisms. For instance, an early study by Ishii et al., (2016) implemented the M2M internet of things including a machine-to-machine-based system to early detect dementia symptoms mostly in elderly people. Behavioural data and early symptom data were collected through the sensor mounted in the house of the elderly. The data were compared and evaluated through a questionnaire by the new system, hence, the system detects the absence or presence of dementia. A more recent study by Kwan, Cheung, & Kor, (2020) used a smartphone with a voice navigation control system to determine the physical functioning and optimum free-living surrounding people experiencing mild dementia. However, its system requires an improvement in terms of efficacy and security to promote the outdoor independence of the users. Furthermore, home-based sensor technology such as ambient sensor and body-mounted were deployed to manage their daily activities living of dementia which recorded high accuracy by decreasing cognitive impairment in the older people (Urwyler, Stucki, Rampa, Müri, & Mosimann, 2017). Emerging technology has contributed immensely to the management of dementia. For example, a smartphone with electronic memory aids improves long-term memory deficits, which helps in managing the semantic dementia associated challenges and have a smart living (Bier, Paquette, & Macoir, 2018).

Table 5. Disease Diagnosis domains, description, and sensor used.

Application Domains	Description	Example of sensor used	Authors
Coronavirus disease contact tracing and testing (COVID-19)	The novel virus causes serious illness and threatens human life existence thereby leading to untimely death. Hence, has become a global pandemic and transmitted from body contact	GPS, proximity, and ambient light sensor	(Alo et al., 2022; Aminian et al., 2020; Maghdid et al., 2020; Schuller et al., 2020; Sun et al., 2020)
Human activity identification	This involves daily life exercises and actions such as hamstring exercises	Accelerometer, gyroscope, ECG, pedometer, magnetometer, EMG, temperature sensor, and pulse oximeter sensor	(Beevi et al., 2016; Chen & Wang, 2017; Hegyi et al., 2019; Jin et al., 2014; Juen et al., 2014; Lee et al., 2014; Lim et al., 2020; Michelsen et al., 2020; Sodhro et al., 2018; Spinsante et al., 2016; Sundaravadivel et al., 2017; Syed et al., 2019; Thaung et al., 2020)
Sleep disorder and sleep stage detection	General recurring physiological activity. Hence, lack of quality sleep affects human health. It is associated with diseases such as insomnia and obstructive sleep apnea	SPO_2, PPG, BCG, and EEG sensor	(Br, 2014; Dey et al., 2017; Haoyu et al., 2018; Robbins et al., 2018; Zhang & Wu, 2017)
Fall detection	Fall constitute the foremost causes of injury, disability, and possibly death in an individual especially the elderly or aged people	ECG, accelerometer, gyroscope, and magnetometer sensor	(Giuberti et al., 2015; Hakim et al., 2017; Lee et al., 2014; Lee et al., 2018)
Bipolar disorder detection or social anxiety	Associated with mental related illness. The signs include common successions of periods of manic, normal, and depressive state	Accelerometers, GPS, and gyroscope sensor	(Abdullah et al., 2016; Gr et al., 2014; Y. Huang et al., 2017)
Motion state and stress detection	Involves human physiological mental stability and unstable state which might result in a degree of misjudgment. It affects the state of mind especially when receiving shock information	EEG, PPG, accelerometer, heart rate and SPO_2, blood pressure, and temperature sensor	(Wannenburg & Malekian, 2015; Xu & Plataniotis, 2016; Zhou, 2020)

Application Domains	Description	Example of sensor used	Authors
Psychiatric detection	Mental health disorders affect the state of the mind and brain thinking faculty. It leads to a complex mental illness called Schizophrenia when it is not detected and treated on time	Pedometer, accelerometer, acoustic, GPS, and light sensor	(Ben-zeev et al., 2015; Difrancesco et al., 2016; Wang et al., 2016)
Depression and mood swing	Mental health disorder. It is associated with impaired daily functioning and worsening of co-morbid medical illness	Accelerometers, gyroscope, magnetometer, and proximity sensor	(Asselbergs et al., 2016; Canzian & Musolesi, 2015; Jaworska et al., 2019; Ray & Agarwal, 2019; Saeb et al., 2015)
Parkinson diseases	The neurodegenerative disorder affects mostly aged people between 65years and above. It related non-motor symptoms that complement to overall disability	EEG, and ambient light sensor	(Giuberti et al., 2015; Poewe et al., 2017; Ray & Agarwal, 2019; Trister et al., 2016; Zhan et al., 2018)
Cardiac disease management	This is a disease of the heart. Its management comprises total care using various strategies, approaches, implemented to address cardiac diseases such as heart failure, hypertension, high blood pressure, heart rate, pulse rate, etc.	PPG, ECG, SCG, pulse oximeter, and pedometer	(Bánhalmi et al., 2018; Deshpande & Kulkarni, 2017; Dey et al., 2017; Du, 2016; Elgendi et al., 2018; Essalat et al., 2016; Etiwy et al., 2019; Harris et al., 2019; Iftikhar et al., 2018; Kakria et al., 2015; Maghdid et al., 2020; Mena et al., 2018; Nair et al., 2018; Nam et al., 2016; Neyja et al., 2017; Poplas & Stani, 2016; Sahoo et al., 2017; Stafford et al., 2016; Wannenburg et al., 2018)
Disease diagnosis and wellbeing	Diagnosing and monitoring of disease and general wellbeing of individual periodically is very important even when you are not sick or ill. Applying proactive measures to check your body system health status against undeveloped disease	Heart rate, pulse oximeter, ECG, SpO2, EMG, body temperature, blood pressure, PPG, accelerometer, and humidity sensor	(Abdulghaffar et al., 2019; Al-khafajiy et al., 2019; Debauche et al., 2019; Dur et al., 2019; Janani et al., 2020; Nedungadi et al., 2018; Santhi et al., 2017; Sener et al., 2019; Simjanoska et al., 2018; Swaroop et al., 2019; Verma et al., 2017; Wang et al., 2018; Wu et al., 2019; Yu et al., 2018)
Neurological disease monitoring	Involves a varied group of disorders that are associated with progressive degeneration in	ECG, EEG, accelerometer, and gyroscope	(Gong et al., 2016; Kuusik et al., 2018; Poewe et al., 2017; Subasi et al., 2020)

Application Domains	Description	Example of sensor used	Authors
	terms of structure and function of the central nervous system.		
Diabetes retinopathy	Diabetics are associated with clinical manifestations of metabolic syndromes, such as hypertension, dyslipidemia, and obesity, which affect organs and body systems such as the heart, blood vessels, kidneys, nervous system, etc.	Glucometer and blood pressure sensor	(Badar et al., 2020; Chhiba, 2019; Kumar et al., 2018; Jie Li et al., 2019; Sharma et al., 2016)
Posture monitoring	Involves different aspects of the body position. Bad placed posture causes pains and decreases the flexibility of the joints making it prone to injuries	Accelerometers, gyroscopes, and pressure sensor	(Acharya et al., 2019; Roh et al., 2018)
Dementia detection and management	It is a syndrome that is characterized by symptoms associated with progressive brain dysfunction and total impairment of cognition. It causes Alzheimer's disease	Passive infrared, blood pressure, heart rate, and body temperature sensor	(Acton et al., 2018; Bier et al., 2018; Ishii et al., 2016; Kwan et al., 2020; Urwyler et al., 2017)

6. Challenges and Solutions

Various challenges are threatening the efficient running and monitoring of human health status. The utilization of m-Health, sensor-based technology, and management of the healthcare system has faced enormous challenges, which we set to discuss and proffer solutions to each of them.

6.1 The Major Challenges

The identifiable challenges include lack of contact tracing and testing smart devices for human health monitoring, inadequate tools for disease diagnosis and prediction of wellbeing, lack of infrastructural facility, power consumption and management, difficulty in communication and computation, and security and privacy issues. Nonetheless, these challenges are discussed below:

(i) Lack of contact tracing and testing smart mobile apps for human health monitoring

There is insufficient contact tracing and testing smart devices for disease monitoring in our healthcare environment today. This has affected or halted effective healthcare service delivery. For instance, recently the pandemic novel coronavirus disease is killing millions of people in the world and challenging the medical practitioner on the possible way to curtail it (Aminian et al., 2020). The rapid increase in transmission from affected patients to uninfected persons is a result of inadequate testing devices such as smartphones with heterogeneous sensors to strategically and dynamically trace the primary and secondary contact person to curtail the widespread of life-threatening diseases.

(ii) Inadequate tools for disease diagnosis and prediction of wellbeing

Technological tools for disease diagnosis and prediction of wellbeing are limited. The healthcare centre, healthcare provider, and doctors require new technology devices to dynamically diagnose and treat abnormal health disorders, chronic diseases, and life-threatening ill health such as COVID-19, cardiovascular disease, Parkinson disease, neurological disease, diabetes retinopathy, lung cancer detection. Most of our healthcare system today lacks new tools and technology such as wearable sensors-based technology, smartphones, the internet of medical things, etc. for early diagnosis and treatment of patients and monitoring of general wellbeing of an individual. For instance, elderly people suffer from health monitoring status as a result of a lack of an automated platform to communicate with doctors and healthcare providers remotely (Al-khafajiy et al., 2019).

(iii) Lack of infrastructural facility

People living in rural areas cannot benefit from preventive health services due to a lack of infrastructure and technological mechanisms to tackle some menace in healthy living. Our healthcare today lacks basic facilities, human skills, technological tools, and intervention from the healthcare givers which have left the healthcare system to deteriorate. People suffered a lot to access the amenities when sick. For example, recently, the pandemic novel infectious diseases such as coronavirus (COVID-19) (Aminian et al., 2020; Giudicessi, Noseworthy, Friedman, & Ackerman, 2020; Schuller et al., 2020) has affected over 200 countries due to a lack of infrastructure and healthcare equipment such as beds, testing kits, ventilators, temperature monitor, etc. These have led to unprecedented mental health disorders, health challenges, and deaths in our community (Ayón, 2018).

(iv) Power consumption and management

An effective health monitoring system requires long-lasting power or battery management. Mobile and wearable devices mostly use battery and somewhat power to carry out and stand a taste of time while deploying for either testing, diagnosis, analysis, or monitoring both proximity and remotely. Power or battery drainage affects the real-life deployment and implementation of the efficient healthcare system. Wearable devices' power consumption (Ching & Singh, 2016) drastically affects the wearable devices such as sensors, mobile and communication devices. For instance, some battery power of wearable devices don't last longer, therefore, affecting the normal operation of devices, hence, it causes and reduces utilization and adoption by the users.

(v) Difficulty in communication and computation

There exist an amount of delay in communication from one sensor or device to another device in a host which affects the processing time. The computations in the wearable device allow the host device to flexibly eliminate the unnecessary sensing data normally exhibit with "rule". Therefore, reduce the overhead of data communication in the system (Ching & Singh, 2016; Uddin et al., 2015).

(vi) Security and privacy issues

Health is associated with security and privacy issues especially in the involvement of smartphone devices (Cornet & Holden, 2017). A lot of people don't want their health status or history to be disclosed to the public for security reasons. The security and privacy of data generated and analysed from homogeneous, dual, and heterogeneous sensors and mobile-based technology need maximum protection. Even though various research has been carried out to improve and restore the confidence of people or patients' data, however, the security and privacy are still inherent and have generated much health concern among the medical practitioner and the users. Mobile and sensor utilization in monitoring human health systems has security issues due to data communication, transferring data from one medium to another, cloud storage, etc. and is associated with high risk and prone to attack by unscrupulous elements (hackers and scammers), viruses, and other cyber-physical attacks. Take, for example, information collected may be a target of an unauthorized or illegitimate person particularly for healthcare data that require extreme levels of security and privacy. In addition, security and privacy issues are still posing threat to the existence of wearable devices and it is yet to be resolved. Nonetheless, security privacy issues have become a degenerative issue that has been highlighted by several authors. Some of these issues include insecure data storage on the cloud, lack of authentication and authorization, software cloud communication and data loss, lack of physical security (Ching & Singh, 2016; Seneviratne et al., 2017; Shrestha & Saxena, 2017). Because of these, users' trustworthiness towards usage of wearable devices such as smart-watches, eyeglass, head-worn, and other smart devices such as smartphones decreases thereby affecting the effective health monitoring system.

6.2 Solution to the inherent challenges

Owing to the imminent challenges facing wearable devices used for health monitoring systems, challenges are becoming a recurrence decimal, hence, we suggest different measures or solutions to address the immediate challenges as discussed in section 3.4.1. These include

(i) Adequate contact tracing and testing smart mobile apps for human health monitoring

This can be addressed through the design, implementation, and deployment of smartphones interconnected with the internet of things that could enable primary and secondary contact tracing of infected or suspected cases would reduce the spread of the disease. The government and other health agencies such as World Health Organization (WHO), non-governmental health support, and even Nigeria centre for disease control (NCDC) etc. need to work in collaboration to acquire a sufficient number of mobile devices and make same available to the public for self-test and early detection of the diseases, which will in-turn assist in the fight against the diseases such as COVID-19. Smartphones play a vital role in the contact tracing of the COVID-19 pandemic, although, only a few designs are available (Leith & Farrell, 2020; Maghdid et al., 2020).

(ii) Provision of tools for disease diagnosis and prediction of wellbeing

We need a holistic approach to solve this challenge that is dilapidating and degenerating and deteriorating our health centre. Government agencies need to work in partnership with private institutions and well-meaning individuals to provide enough tools and smart medical devices to improve the healthcare service delivery in every locality.

(iii) Provision of infrastructural facility

For our healthcare system to improve, it requires a concerted effort from the government, private organizations, non-governmental organizations, and well-meaning philanthropists. However, the government has a big role to play by making provisions and investing more in the health sector, yearly budget in healthcare need to increase, adequate provision of all necessary basic infrastructural facilities will ameliorate the health daily living of our people. Embracing information and communication technology equipment such as wearable sensor devices, networks, IoMT and IoT devices components, smartphones, etc. will efficiently add to the improvement and enhancement of our medical healthcare system and to ensure effective health monitoring of an individual.

(iv) Improve power consumption and management

The power requirement of the system can be satisfied by using low power components, more efficient batteries, or by employing energy harvesting techniques. Also, battery life can be improved by ensuring the sleep and wake-up of the sensors in a timely fashion without disrupting the desired measurement frequency (Majumder & Deen, 2019). In addition, the miniaturization of wearable sensors and smartphone devices other medical component devices can reduce power utilization. Furthermore, they should be the provision of alternative power banks, conservation of energy, and rechargeable batteries to support the power consumption of the healthcare device system.

(v) Effective Communication and computation

In order to achieve communication and computation, there is a needs to evaluate the trade-off between the amount of computation and the reduction of data communication in the healthcare system. It will deliver efficient interoperability of the wearable sensor devices, internet of things, and mobile phones for effective computation. Recently, a framework for human activity monitoring to solve the problem was developed (Uddin et al., 2015). The researcher achieved light computation tasks on the wearable device to reduce the amount of data communicated between the wearable, and its host. Though still lack efficiency and computational time to holistically provide a solution for communication and computation of data sensing from the network.

(vi) Implementation of security and privacy

Recently, a lot of effort has been made to provide lasting security and privacy measure to ensure user or patient's security and privacy of data and health status. A high level of security and privacy is to be maintained between the healthcare givers or doctors and the system user or patient in the healthcare centre. The reliability, authentication, control access, and policy need to be practiced and put to use. A lot of authors have implemented different security measures and privacy control mechanisms to address the recurring menace challenging the efficient development of health monitoring systems. These measures include the private key, authentication, encryption, a clustering K-Anonymity privacy-preserving approach, username and password mechanism, block-chain technology method, and hybrid security model, etc. (Ching & Singh, 2016; Elhoseny, Ramírez-gonzález, Abu-elnasr, Shawkat, & Arunkumar, 2018; Liu & Li, 2018). Also, the effective implementation of 3D touchscreen and microphone sensors authentication-based approach (Lazam, Zaidan, Zaidan, Albahri, & Alamoodi, 2020). However, more research is ongoing to extremely provide hybrid solutions to restore security and privacy in the human healthcare system.

7. Discussions

This study extensively reviewed academic articles on mobile and wearable devices for health monitoring published from January 2014 to December 2020. In a nutshell, the study is categorized into five sections. These include sensors for health monitoring, system architecture for health monitoring, application areas, challenges, and solutions.

The findings of these thorough reviews show that mobile and wearable devices have been widely deployed for various health monitoring. The wearable sensors have been utilized for various health monitoring, hence, from our findings, we discovered that sensors are classified into three auspicious, namely; homogenous (single) sensors (Krishna et al., 2020; Michelsen et al., 2020; Wannenburg et al., 2018; Zhou, 2020), dual (two) sensors (Acharya et al., 2019; Bánhalmi et al., 2018; Iftikhar et al., 2018), heterogeneous (multi) sensors (Debauche et al., 2019; Thaung et al., 2020; Wang et al., 2016; Wannenburg & Malekian, 2015). In addition, 41 out of 85 primary papers utilized homogenous sensors for the health monitoring system. Nonetheless, 21 out of 85 primary papers deployed dual sensors only for effective implementation and deployment of human health monitoring systems. Moreover, in our broad review, we discovered the need to combine more than one sensor to implement a cost-effective health monitoring system. Hence, 17 studies out of 85 primary papers saw the need to combine more than two sensors for effective implementation and deployment of human health monitoring systems. Multiple sensors usage is necessitated for a holistic approach in providing a solution to various health state challenges ravaging human existence.

This study identified system architecture as a based block for health monitoring which include, data collection (Subasi et al., 2020), data transmission (Siam, 2019; Syed et al., 2019), data integration (Yu et al., 2018), data pre-processing (Enamamu et al., 2020), feature extraction and data analysis (Alo, Nweke, & Ele, 2021; Kumar et al., 2018; Verma et al., 2017), and evaluation measures (Verma et al., 2017). Therefore, the investigation of the use of architectural components helps in building efficient mobile health monitoring for elderly people and general wellbeing. Furthermore, our findings also indicate that mobile and wearable devices have been employed in numerous areas for health monitoring. These include coronavirus contact tracing (Alo et al., 2022; Tao et al., 2020), human activity identification (Hegyi et al., 2019), fall detection (Evangeline, 2018; Hakim et al., 2017), Parkinson diseases detection (Poewe et al., 2017; Ray & Agarwal, 2019), and disease diagnosis and wellbeing (Nedungadi et al., 2018; Yu et al., 2018).

However, the review observes some challenges that have affected the effective development and utilization of mobile and wearable devices for effective human health monitoring. Some of these challenges include lack of contact tracing and testing smart mobile apps (Aminian et al., 2020), inadequate tools for disease diagnosis and prediction of wellbeing

(Al-khafajiy et al., 2019), lack of infrastructural facilities (Ayón, 2018), and security and privacy issues (Cornet & Holden, 2017). Nevertheless, the study identified some solutions adopted to overhaul the challenges. These measures include adequate contact tracing and testing smart devices, provision of tools for diseases diagnosis and predictions of wellbeing, and implementation of security and privacy.

8. Future Prospects

Recently, the utilization of sensor technology such as homogeneous, dual, and heterogeneous sensors integrated with the internet of things (IoT), and internet of medical things (IoMT) have changed our human healthcare monitoring system to increase the diagnosis, treatment, prevention, rehabilitation, robustness, and performance accuracy of the mobile healthcare monitoring system. A reasonable number of studies, measures, methods, techniques, approaches and smart mobile-based applications with sensor modalities have been implemented. In mobile-based applications for human healthcare monitoring, system architectural methods such as data collection process, data transmission, data pre-processing or de-noising, data analysis, feature extraction, and evaluation measures were utilized to propose a framework with built-in sensors to effectively diagnose, predict and monitor human health. Integration of mobile-based application with sensor modalities for health monitoring to enable various human health diagnoses, testing, treatment, prevention, and effective monitoring of human health challenges such as coronavirus disease (Alo et al., 2022; Tao et al., 2020), human activities (Hegyi et al., 2019; Michelsen et al., 2020), sleep disorder or stage detection (Zhang & Wu, 2017), fall detection (Lee et al., 2018), bipolar disorder detection or social anxiety (Abdullah et al., 2016), motion state and stress detection Zhou et al., 2020), psychiatric detection (R. Wang et al., 2016), depression and mood swing (Jaworska et al., 2019), Parkinson diseases (Giuberti et al., 2015), cardiac disease management (cardiovascular) (Etiwy et al., 2019; Harris et al., 2019), disease diagnosis and wellbeing (Nedungadi et al., 2018; Yu et al., 2018), neurological disease monitoring (Subasi et al., 2020), diabetes retinopathy (Kumar et al., 2018), and posture monitoring (Acharya et al., 2019). Comparative analysis of some of the studies in mobile and wearable sensor-based health monitoring is shown in *Appendix A*. Mobile-based applications features provide a platform to combine different analysis and visualization means which are highly needed in human healthcare monitoring due to their interpretation natures. In mobile-based application implementation and interpretation, machine learning algorithms such as support vector machine (SVM), decision-tree, K-means, Naive Bayes, neural network, random forest, etc. play vital roles, combining and analysing the extracted data from sensor data to predict optimum healthcare status.

However, the recent research efforts in mobile healthcare monitoring systems have led to future research prospects that can be further pursued by researchers in technology-based health domains. These include:

(i) Contact tracing and testing for human health monitoring

Contact tracing and testing of contacted persons using smartphone-enabled heterogeneous sensors require to indebt research (Bashir et al., 2020). It is necessary to develop integrated technological application frameworks that can unify tracing and tracking of the remote location of a person, testing, and offer a prediction about the suspected person or patients. For instance, in the aspect of coronavirus disease (COVID-19) (Maghdid et al., 2020) handled by the health officers, many contacts of the affected or confirmed cases were subjected to the isolation treatment centre to expedite tracing of both primary and secondary contact, hence, require smart devices to effectively trace and test the patients, instead of implementing a total lockdown of the region. Mobile and sensor technology play vital roles in tracing and testing ill patients thereby increase the optimum human healthcare system service delivery, hence, it requires smart integrated technology such as IoT, smartphone, IoMT, Wi-Fi, BLE etc. Also, more enhancement and full implementation of real-life contact tracing of novel COVID-19 and other deadly disease with smartphone applications utilizing the BLE (Bluetooth Low Energy) (Leith & Farrell, 2020) to solve the pandemic diseases ravaging the world.

(*ii) Disease diagnosis and prediction of wellbeing*

Smartphones and sensors technology contributed to the human health monitoring of different diseases, viruses, and mental health disorders. Diseases diagnosis and prediction of the health status of an individual both the young and the elderly are very important in order to improve their daily life activities (DLA). A lot of research works have been carried out to develop and implement a strategy, framework, algorithms, methods, and cost-effective system to solve human health challenges. However, much research is needed to holistically build an effective mobile health system (m-Health) to diagnose and monitor the human health system. For instance, to develop and enhance Wearable Sensors for Smart Healthcare Monitoring System (SW-SHMS) for elderly people using a predictive approach such as machine learning (Al-khafajiy et al., 2019), integrate an Nvidia Jetson Nano to Smart Gateway with Artificial Intelligence for data filtering, abnormal value detection, and drifting sensors. Also for abnormal behaviour detection using machine learning techniques (Debauche et al., 2019), the inclusion of wearable sensors such as gyroscope, magnetic sensor, angular velocity sensor, etc. for auxiliary detection in health monitoring systems with regards to human motion state recognition (Zhou, 2020), to implement the algorithm with a higher population of CVD patients having various cardiac disorders as well as a randomized clinical trial of CVD screening using a phone for reliability (Iftikhar et al., 2018). In addition, develop affordable techniques for diagnosis and preventing arrhythmias diseases in the clinical centre for the elderly (Mena et al., 2018), and full implementation of an enhanced technique for automatic sleep stage detection anomaly with regards to EEG using complex convolution neural network (CCNN) (Zhang & Wu, 2017).

(iii) Human activity monitoring

In human activity monitoring (HAM), m-Health has recorded an impressive achievement. Various human daily activities have been detected and monitored to improve the mental health of individuals. Full implementation and deployment of mobile and sensor technology improve the detection rate of falls, physical activities, and posture of an individual to reduce the health risk. However, more concerted research efforts are suggested to build effective human healthcare monitoring system as follows: (a) develop and improve the precision of the smartphone utilizing tilt sensor and other baseline sensors for effective fall detection (Y. Lee et al., 2018), (b) to examine the clinical implications and functional relevance of heterogeneous hamstrings EMG activity (Hegyi et al., 2019), (c) to expand the entire posture monitoring using ATmega328 and smartphone (Acharya et al., 2019), (d) to investigate the posture variation such as changes of foot position, armrests, seat height and to provide an optimal sensor position with sitting posture monitoring system using fewer sensors and algorithms as well as classification technique (Roh et al., 2018). In addition, to develop more complex mobile applications which can record human activity recognition and higher dataset (Spinsante et al., 2016).

(iv) Integration of health technology devices and data unification

The combined action of the internet of things, sensors technology, and smartphone with data generated from them, etc. has led to the effective development of the healthcare delivery system. Integration of different devices and communication technology such as sensors, mobile phones, mobile applications, wireless networks, Bluetooth, body area network, Wi-Fi connections, etc. to share and transmit data has contributed much impact in the healthcare services today. Recently, patients and healthcare providers including doctors can conveniently interact with each other while they are at home, the doctor can collect the user data, analyse and infer a result for further treatment and recommendation. Their health status and physiological data can be monitored remotely without physically being present. Consequently, due to the heterogeneous and divergence nature of this technology, more features, updates, components, and applications are emerging and converging daily, hence, it requires further studies in order to enhance and improve the smooth running of our healthcare system. Area of further attention is drawn in this aspect as follows (a) Develop robust feature engineering with regards to Mobile phone-based unobtrusive Ecological Momentary Assessment (EMA) using machine learning approach or other baseline prediction mechanism (Asselbergs et al., 2016), (b) Enhancement of system mechanism for GPS data in schizophrenic patients (Difrancesco et al., 2016), (c) Develop self-signal processing for super-precision health check using deep learning and inertial sensor data and other clinical data (Gong et al., 2016), and (d) To develop a robust software platform to detect any ECG pattern and signal in case of any health condition that should be able to communicate to the healthcare provider or doctors through a message via e-mail or SMS notification or any web-based alert especially in time of critical early detection of critical patients (Mishra, 2018), (e) Integrating Smart IoT-gateway with regards to multiple wireless devices and carry out faster edge computing (Wu et al., 2019).

(v) Security and privacy

The security and privacy of data generated and analysed from homogeneous, dual, and heterogeneous sensors and mobile-based technology need maximum protection. Even though various researches have been carried out to improve and restore the confidence of people or patients' data, however, security and divulgence are still inherent and have generated many health concern that requires a collective effort to solve them. Mobile and sensor utilization in monitoring human health systems have some security measures (Masoud et al., 2019) but because of data communication, transferring data from one medium to another, cloud storage, etc. It is associated with high risk and is prone to attack by unscrupulous elements (hackers and scammers), viruses, and other cyber-physical attacks. For instance, information collected may be targets of an unauthorized or illegitimate person particularly for healthcare data that require extreme levels of security and privacy. More research efforts are suggested to build a reliable and effective healthcare system. Some advanced areas include (a) Development of Kalman and filter adaptive to truncate noise in healthcare centre using ECG signal as biometric security measures for telemedicine practice (Sodhro et al., 2018), (b) Implement real-time security technique in medical data on cloud database using cryptographic algorithms (Kumar et al., 2018), (c) To improve on the security and other functionalities in utilizing Internet of Things to monitor multiple diseases in the health system (Abdulghaffar et al., 2019), and (d) Implement real-time authentication mechanism based 3D touchscreen and microphone sensors for mobile health (Lazam et al., 2020).

(vi) Mobile cloud applications and internet of things implementation

Implementation of mobile cloud apps based on health activity and ambient daily living as a service and IoT, connected through the internet service provider to support various and community mobile-based applications and health monitoring for an elderly and well-meaning individual is of great need today (Alo et al., 2020). The current mobile-based apps for detection and health monitoring provide less interoperability, compatibility, scalability, and are very difficult to survive for total m-Health monitoring. Therefore, implementation of interjectory of these two sensitive domains; IoT and mobile-based human health monitoring will enable the combination of varied heterogeneous sensors for remote and automatic data collection, data transmission, processing, and analysing mobile-based applications for human health monitoring.

Moreover, higher improvement to ensure efficient health monitoring by utilizing the mobile and heterogeneous sensor technology (Nweke et al., 2019; Nweke, Teh, Mujtaba, Alo, & Ali, 2019).

(vii) Power management and consumption

An effective health monitoring system requires long-lasting power or battery management. Mobile and wearable devices mostly use battery and some other power to carry out and stand a taste of time while deploying for either testing, diagnosis, analysis, or monitoring both proximity and remotely. Power or battery drainage affects the real-life deployment and implementation of the efficient healthcare system. Battery miniaturization and power saver with mobile and wearable devices call for further research for the sustainability of the healthcare service delivery to the common people. For instance, build prototypes of human body communication channel and combine sensors to Simulink in order to minimize power consumption in body area network (BAN) (Sundaravadivel et al., 2017).

9. Conclusion

In conclusion, mobile health monitoring systems are very important in human health, living, and development. The wearable sensor is a fundamental part of the new telemedicine paradigm designated to support the perception that quality healthcare delivery services will improve through the utilisation of effective information and digital health devices. The use of wearable sensors has made effective disease diagnosis simple and has assisted in monitoring and treatment, hence we reviewed mobile and wearable sensors for the health monitoring system. First of all, we highlighted the need for monitoring of health status of an individual in this contemporary era. Therefore, we reviewed sensors for health monitoring systems into three auspices; homogeneous sensors, dual sensors, and heterogeneous sensors. Furthermore, we discussed system architecture for health monitoring which consists of data collecting process, data transmission, data integration, data pre-processing (de-noising), feature extraction and data analysis, system architecture evaluation measures. More so, we presented the main application areas of mobile and sensor technology such as coronavirus disease contact tracing and testing, human activities, sleep disorder or stage detection, fall detection, bipolar disorder detection or social anxiety, motion state and stress detection, psychiatric detection, depression and mood swing, Parkinson diseases, cardiac disease management (cardiovascular), disease diagnosis and wellbeing, neurological disease monitoring, diabetes retinopathy, and posture monitoring. In addition, we point out the main challenges and suggest solutions measures to address the inherent problems facing the effective implementation and utilization of mobile and wearable sensors in the healthcare system. We further presented the open research challenges to alert the interested researchers in these areas. These include contact tracing and testing, disease diagnosis and prediction of wellbeing, human activity monitoring, integration of health technology devices and data unification, security, and privacy, mobile cloud applications and internet of things implementation, power management, and consumption.

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Appendix A: Comparative analysis of some recent studies that implement mobile and wearable sensors for health monitoring, their objectives, challenges and proposed solutions.

Study	Objective	Problem Solved	Sensors	Domains	Issues	Solution	Future prospects
(Jin et al., 2014)	Presents walking-age pattern analyzer and means of identification using sensors	Inaccessible and difficulty in attending to walking-age elderly	3-D accelerometer and a gyroscope	Human activity identification/ Walking-Age	Inadequate walking-age data	Provision of gait features and real walking-age	To implement advanced clustering and classifying approach
(Juen et al., 2014)	Develop GaitTrack based software to detect health status of patient using sensor to monitor different human activities	Inaccurate use of medical accelerometers	Accelerometers	GaitTrack for free-living environment	Insufficient digital device models for monitoring and analysis	Building smart model device for human health monitoring and analysis	Develop advance gait model for continuous health status monitoring
(Gr et al., 2014)	Develop smart-phone platform embedded with sensor in tackling psychiatric care.	Difficult in everyday-life monitoring of mental ill patient	Accelerometers , GPS, and gyroscope	Bipolar Disorder Patients	Monitoring of mental illness is complex due to variance in behaviour	Build an efficient smart devices with sensors for monitoring	Advance development of real-time smart aided devices with sensors for bipolar disorders
(Ben-zeev et al., 2015)	Understudy multimodal smartphone sensors generated can serve as behavioural markers for one's mental health	Late sensitive and detection of mental health	Accelerometers , ambient light	Psychiatric detection	Lack of smart and real-time devices enabled sensors	Availability of smartphone enabled sensors	Explore interjectory discipline to create smartphone sensing techniques
(Saeb et al., 2015)	To determine daily-life behavioural signs with the help of mobile phone GPS and wearable sensor	Increase of undetected and untreated mental ill patients	Accelerometers , GPS, gyroscope, magnetometer, proximity	Depressive symptom	Difficult in detecting and treating mental health disorder	Development of smart mobile devices	Cross-validation in large-scale of depressed people based on one's pattern of movements

(Wannenburg & Malekian, 2015)	To implements basic functionality for continuous mobile health monitoring to measure important signals	Lack of basic features and functionality for mobile health monitoring	PPG, Heart rate and SPO_2, blood pressure, and temperature	Stress	Unattained interactive and basic mobile smartphone features	Advance development of full features in mobile smartphone	Implementation of blood pressure estimation for effective calibration method
(Spinsante et al., 2016)	Presents components of HAR to identify signal filtering and windowing solutions for physical activity monitoring solution	Complexity in testing of classifiers during physical activity monitoring in workplace	Accelerometer	Physical activity such as walking, sitting	Ineffective recording and monitoring daily activities via mobile and HAR	Utilizing smartphone and HAR to identify daily physical activities signals	Develop more complex mobile application which can record HAR and higher dataset
(Saeb et al., 2016)	To ascertain and replicate the extend other works utilizing GPS sensors in order to know sever depressive symptom	Lack of mobile features to detect depression mood	GPS	Depressive symptom	Development of smart devices to detect average depression mood is quiet challenging	Develop reliable sensor enabled devices to passively detect depression	develop advance full system with sensor-based evaluation to detect and identify risk of depression
(Wang et al., 2016)	Present randomized control trial of CrossCheck for outpatients with schizophrenia	Difficult in detecting mental ill health patient in early stage	Accelerometer, Acoustic, GPS, light sensor	Schizophrenia detection	Lack of prediction tools	Using full functional devices for passive monitoring	Develop advance CrossCheck system for effective monitoring and prediction
(Verma et al., 2017)	Develop framework for m-healthcare disease diagnosis using fog assisted IoT to predict severe diseases	Challenges of dependently relying on limited storage and computation resources of handheld devices	Blood pressure and ECG/EEG	Disease diagnosis	Lack framework for IoT disease diagnosis and prediction	Develop and equip smart IoT system for severe disease diagnosis prediction	Present new system methodology to compare with other standard and offer theoretical basis

(Sahoo et al., 2017)	Implement an early warning system in cardiac data acquisition approach to monitor cardiac people	High rate of death of corona heart disease as a result of increase in healthcare services	ECG and SCG	Cardiac Early Warning	High cost of healthcare services and infrastructure to monitor cardiac people	Development of an efficient system to monitor cardiac patients	Develop an analysis techniques to detect and improve the accuracy of cardiac abnormalities
(Deshpande & Kulkarni, 2017)	To implement health monitoring system to detect quick abnormalities of health conditions	Lack of infrastructural facility to monitor health related conditions	ECG	Heart disease	High cost of medical devices	Provision of medical devices and develop monitoring system	Build an efficient ECG monitoring system to detect heart diseases related issues
(Sundaravadivel et al., 2017)	Present an architecture for an ambulatory health monitoring system using a body coupled communication channel	Increase in power consumption	Temperature, Proximity and Gyroscope sensor	Ambulatory	High energy consumption	Improve power consumption	Build prototypes human body communication channel with sensors to minimize power consumption in BAN
(Wannenburg et al., 2018)	Design of wireless wearable system for measuring ECG and respiration rate	Unobtrusive continuous health monitoring using mobile devices	ECG	Respiration rate	Limited sensor usage for continuous health monitoring	Obtrusive mobile continuous health monitoring	Employ optimisation on the surface mount level of the wearable devices
(Lee et al., 2018)	Implement real-time fall detection system which detect individual falling and notify the administrator	High rate of injury in elderly as a result inability to detect fall early	Accelerometer	Fall (physical activity)	Lack of medical care and tools to detect falls in elderly people	Improve power and utilization of technology tools to detect falls	Increase the precision of the technological device's tilt sensor and fall detection

(Yu et al., 2018)	Presents an integrated and efficient platform mechanism for effective monitoring of wellness of elderly people in Hong Kong	There is no presence smart system intelligently and integrated with the health provider	PPG and accelerometer	Elderly Wellness	Inefficient framework to process and integrate and collect data from varied sources	Develop an efficient platform to integrate data from different sources for health monitoring	To implement and scale to engage large number of elderly in centralize form
(Nair et al., 2018)	To develop prototype of a wearable fitness band	Irregular physical activities	Pedometers	Cardiac emergency conditions detection	Inconsistent walking detection for wellbeing	Deployment of wearable fitness band sensor	Develop database system and real-time system that detect and stores data of tracked physical activities
(Syed et al., 2019)	Develop smart healthcare framework for AAL to monitor the physical activities of elderly people using IoMT and intelligent approach for enhance treatment recommendations.	Lack of technological mechanism to monitor the health being of elderly people	Accelerometer, gyroscope, magnetometer, and ECG	Physical activities for elderly people	Inadequate caregivers to aging people and fall prone	Develop smart and integrated technological in the healthcare centre	Develop advance real-time healthcare framework for AAL to monitor the aging people
(Swaroop et al., 2019)	Presents designing of a real-time monitoring system which can store a patient's health parameters.	The envisaged problem is the single mode communication option	Blood pressure and body temperature	Patient's vital signs	Congestion in transmission and communication	Increase the communication channel	Develop framework for real-time analysis and monitoring
(Al-khafajiy et al., 2019)	To develop a smart healthcare monitoring system that observes	Difficulty in providing and accessing home base healthcare	Pulse and oxygen sensor, heart rate and	Patient's disorder	Knowledge domain validation issues	Improve smart technology enabled healthcare	To develop and enhance wearable sensors for smart healthcare monitoring

	elderly patience remotely.	monitoring and hospitalization	blood pressures.			monitoring system	System for elderly people prediction
(Dur et al., 2019)	The authors proposes real-time health monitoring mechanism to achieve better health living of older adults in rural dwellers	Privacy and data security challenge	Heart rate , body temperature, and blood oxygenation	Wellbeing of elderly	Network connectivity bridge	Provide alternative to network gateway for data security and health monitoring	Develop sustainable plan, evaluation and validation in geriatric residences
(Wu et al., 2019)	Develop a hybrid wearable sensor network system with the IoT for monitoring of health safety of an individual	Privacy and data security issues	PPG, ambient temperature, relative humidity, CO_2, body temperature, and UV sensor	Environmental hazard	Complexity in data integration and sharing	Implement real-time security technique in using cryptographic algorithms	Integrating Smart IoT-gateway with regards to multiple wireless devices and carry out faster edge computing
(Zhou, 2020)	Proposes a wearable health monitoring system architecture based on human motion state recognition utilizing daily activities of the human body	Lack of vital information from physiological characteristics and exercise of human state motion	Accelerometer	Human motion state recognition	Only few human motion state recognition was considered	Deploy wearable sensor to monitor enough human state motion	Inclusion of wearable sensor for auxiliary detection with regards to human motion state recognition
(Subasi et al., 2020)	The study presents mobile cloud-based health monitoring system that assess heart related disorders using	Difficulty in continuous and definite remote monitoring of patients with extreme cases	ECG and EEG	Epilepsy	Continuous and precise monitoring of mental disorder patients	Develop real-time and efficient framework integrated	Develop biomedical signal monitoring for abnormal situation detection

	biomedical sensors signal					biomedical sensors	
(Thaung et al., 2020)	Implements an integrated wearable health monitoring platform using sensors technologies to effectively carry out brief data analysis	Complex dynamic change in physiological signals of human body	Heart beat sensor, temperature sensor and pulse oxygen saturation level (SPO2) sensor.	Human activities such as running, walking, and climbing etc	Lack of framework for data analysis	Develop integrated wearable devices for health monitoring	Implement sensor enable platform and data analysis
(Lim et al., 2020)	Implement Muscle Sense method which estimates exercise workload by utilizing wearable sensors and regression analysis	Workload detection during exercise is cumbersome	sEMG	Weight sensing	Detecting workload during training impose big challenge	Develop full functional sensing system to determine the exercise workload	Implement MuscleSense weight sensing approach with multiple sensors
(Michelsen et al., 2020)	To determine whether wearable textile EMG recording systems can be utilize for detection of muscle activity of children and adult during daily activities	Difficulty in detecting change in muscle activity levels for which daily tasks between the old and children	EMG	Children with Cerebral palsy detection involving daily life activities	Complexity in detection cerebral palsy during constant activities	Implement wearable EMG sensor in the textile for effective detection	Full features implementation of wearable textile sensors recording system for detection of muscle activities

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