IoT for Continuous Physiological Parameters Monitoring in Healthcare: A Review

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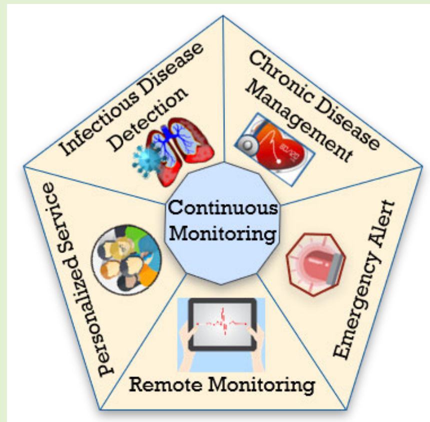
***Abstract*—The use of Internet of Things (IoT) technology in the healthcare system has significantly improved the efficiency and effectiveness of patient care, marking a paradigm shift in modern healthcare practices. Continuous monitoring of physiological parameters through wearable devices has the potential to contribute to the early detection of various chronic and infectious diseases. In this survey, we dig into a variety of wearable devices, exploring the sensors they employ and the specific physiological parameters they monitor. Additionally, we demonstrate the wireless communication facilitated by these devices, connecting sensors and external servers or cloud platforms. Ultimately, we showcase the diverse array of applications for these wearable devices in the realms of disease diagnosis and prevention, achieved through the continuous monitoring of physiological data.**



***Index Terms*—Healthcare, infection detection, Internet of Things (IoT), machine learning (ML), wearables.**

I. Introduction

IN RECENT years, the Internet of Things (IoT) has risen in prominence as a valuable technology due to its ability to provide seamless connectivity for various entities and devices, facilitating simultaneous communication from any location and at any moment [1]. By the end of 2030, more than a trillion "things" (i.e., physical objects with sensors attached) will be connected to the Internet, leading to a significant increase in available data. Knowledge obtained from this data can be utilized in autonomous data management and independent decision-making [2]. IoT is becoming an essential part in the design and implementation of several real-life applications such as smart cities, education, home, healthcare, and various other domains.

A key impact of IoT technology has been in the domain of healthcare. With the consistent rise of global infectious and chronic diseases, there is a growing demand for cost-effective, user-friendly health-monitoring systems for efficient and available medical services for everyone. IoT technologies have significantly contributed to the advancement of e-health systems, making a substantial impact on healthcare [3]. Early symptom detection for infectious diseases has contributed effectively to reducing the burden on healthcare professionals and hospital resources. At the same time, regularly monitoring critical bodily parameters has allowed patients to keep track of their chronic disease and maintain better management of the illness. Hence, continuous monitoring of essential physiological parameters has become an important aspect in the e-health system.

Continuous health monitoring refers to remotely analyzing health data collected at specific (frequent) time intervals. Several wearable devices, sensors, and medical devices are integrated together to collect various information about an individual's vitals, physical activities, and other critical health-related parameters. The collected data is transmitted to a server, edge device, or cloud infrastructure, where analysis can be performed to determine the health status and identify any anomalies. The continuous data stream provides a comprehensive overview of an individual's health status, enabling early disease diagnosis, chronic disease management, and prompt medical advice based on severity [4]. Wearable devices constitute a crucial approach that is generally accepted by patients as well as healthy individuals as a means for collecting continuous health vitals. Continuous health monitoring has the potential to improve the healthcare sector in many ways, including early disease detection, enhanced chronic disease management, personalized healthcare approaches, prompt medical guidance, and remote patient monitoring [5].

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A. Related Work

Several review articles have explored the application of wearable devices and IoT in healthcare, generally focusing on specific health conditions or particular technologies. For instance, [6] primarily reviews advancements in light-to-digital converters (LDCs) for photoplethysmography (PPG), analyzing power efficiency, signal quality, and circuit design techniques. Jegan and Nimi [7] reviewed the quality of signal acquisition, analysis, and processing of biosignals collected from wearable sensors, while Andrade et al. [8] focuses on data acquisition, processing, analysis, and compression, emphasizing reduced network latency without compromising accuracy. Nurmi and Lohan [9] explored various machine learning (ML) algorithms used for analyzing e-health data from sensors. However, it primarily addresses the algorithmic aspects, whereas there are other important factors, such as sensor integration and data fusion in e-health data processing. Similarly, Mohan et al. [10] reviews AI and IoT technologies for elderly fall prevention, emphasizing real-time, long-term monitoring systems that operate without human intervention. While it provides valuable insights into this technology integration, solely on AI–IoT integration, and does not explore other potential technologies or applications in elder care. In another work, Triantafyllidis et al. [11] evaluates smartwatch interventions in healthcare, focusing on their effectiveness across various conditions such as cardiovascular (CV) diseases, diabetes, and mental health. The authors highlight the use of devices like the Apple Watch, Fitbit, and Ticwatch E, analyzing their features, outcomes, and challenges. While the article provides valuable insights into smartwatch-enabled health interventions, it does not offer a detailed comparison of smartwatch models or their specific advantages and limitations.

Another work [12] reviews advancements in computer-aided detection (CAD) systems for automatic diagnosis of congestive heart failure (CHF), focusing on the development of ECG-based CAD systems integrating deep learning (DL) methods to automate CHF detection. This approach offers a noninvasive, cost-effective, and efficient alternative to traditional diagnostic techniques, addressing the limitations of standard CHF diagnostic methods. However, while this work provides valuable insights into CAD systems, it focuses only on CHF diagnosis and does not offer a broader perspective on wearable technologies and their applications in continuous monitoring across other health conditions.

Underlining the advancements in IoT, Qadri et al. [13] highlights advancements in healthcare IoT (H-IoT) systems, focusing on emerging technologies like AI, fog/edge computing, blockchain, and big data to enhance quality of service (QoS). Similarly, Kumar et al. [14] provides a broader perspective, discussing challenges, architecture, and applications of IoT across domains such as healthcare, smart cities, and smart homes, while emphasizing the importance of big data analytics. Another review, Swarupa and Narsimhulu [15], examines the foundation of IoT in healthcare, focusing on personalized health systems and IoT-driven techniques for early illness detection and diagnosis. While these reviews offer significant insights, they primarily address specific technological or domain-wide perspectives, leaving a gap in understanding the role of wearable devices in continuous health monitoring.

B. Research Gap

While several review articles have explored IoT technologies in healthcare, they often focus on specific aspects such as system architecture, security, and privacy challenges [6], [13], [14], without addressing the usability and feasibility of sensor technologies for continuous monitoring. Some reviews discuss continuous monitoring but limit their scope to a single organ or a few specific diseases [10], [12], and lack a broader perspective on multiorgan health tracking or early disease prediction. Others focus primarily on wearable devices, that too either commercial or research-based devices, detailing their working principles, vital sign monitoring, data collection, and communication methods [11], but do not cover their role in disease detection, management, and the broader application of continuous vital monitoring in clinical settings. The need for a deeper discussion on the clinical applications of continuous vital monitoring using wearable devices for disease detection and management is imperative.

C. Contribution

In this work, we provide a comprehensive overview of various types of wearable devices, including both commercial and research-based models, ranging from widely available smartwatches to chest-worn wearables developed in research settings. We review a variety of vital monitoring devices, the technologies used for monitoring these vitals (various wearable sensors), as well as data collection and storage methods, communication protocols, and analysis techniques. Additionally, we explore the application of continuous vital monitoring in disease detection and management, with a focus on chronic disease management, making it more accessible, cost-effective, remote, and enabling timely interventions from healthcare experts. Furthermore, we analyze existing IoT applications, highlighting a unique use case: wearable personal health-monitoring systems for remote monitoring, particularly in the context of COVID-19.

Fig. 1 shows a taxonomy of continuous health-monitoring overview. The description of the article roughly follows this taxonomy. Section II discusses various research challenges faced during the implementation of continuous monitoring. In Section III, we discuss the available types of wearable technologies for continuous health monitoring. Section IV presents an overview of the technological approaches employed in continuous monitoring. Section V discusses the applications of continuous monitoring in healthcare using IoT. We conclude in Section VI.

II. Research Challenges in Continuous Health Monitoring

Continuous health monitoring presents several research challenges that must be addressed for its effective implementation. Fig. 2 shows a brief summary of research challenges

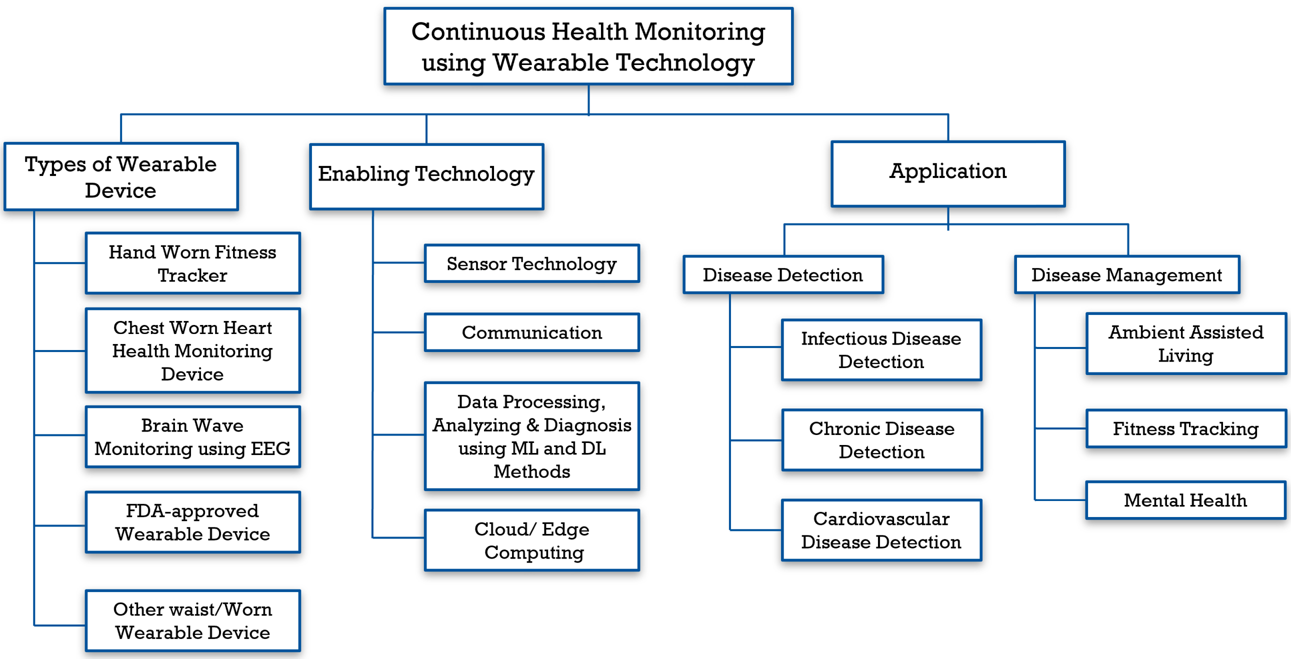

Fig. 1. Taxonomy of continuous health monitoring using wearable technology.

that are frequently encountered while developing IoT-based solutions for continuous physiological parameters monitoring. One significant challenge is managing the large volume of data generated by wearable devices, which can quickly overwhelm storage and processing capabilities. Additionally, adjusting the number of wearable sensors, energy consumption of these sensors, subsequently, the battery size, and the battery life of the wearable device, without violating user-friendliness and comfort, remains a critical concern. Memory complexity and real-time data processing are intertwined issues, as the need for rapid, real-time analysis requires sophisticated memory management and processing power. Moreover, ensuring robust data security in healthcare settings is a top priority, given the sensitive nature of personal health information. Addressing these challenges collaboratively is crucial for the advancement of continuous health-monitoring technologies and unlocking their complete potential in enhancing patient care and overall well-being.

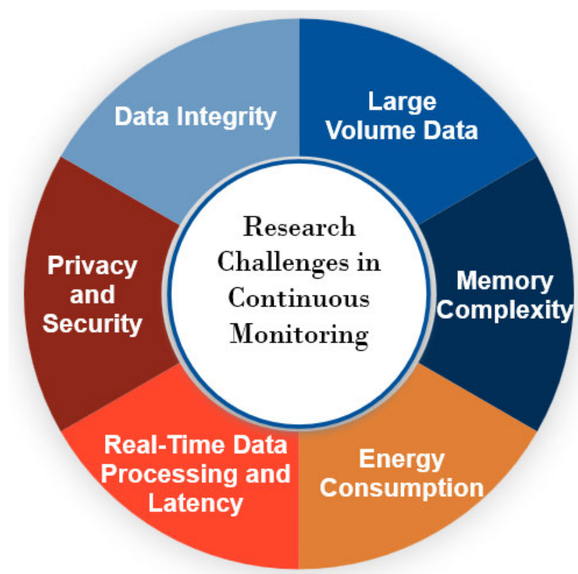

Fig. 2. Research challenges in continuous vitals monitoring.

A. Managing Large Volume of Continuous Data Streams

Various types of sensors are employed at different places to capture distinct physiological parameters from an individual's body. A major challenge in IoT-based healthcare is effectively managing and analyzing the large volume of continuous physiological data collected from the wearable sensors. Continuous data streams from multiple sensors, such as ECG, temperature, and galvanic skin response, create substantial storage, bandwidth, and computational demands [16]. Furthermore, each sensor often employs distinct data formats and sampling rates, complicating data integration and interoperability. This diversity leads to significant challenges, including increased complexity in data fusion, delayed analytics, and difficulties in providing real-time insights [17], [18].

Large-scale continuous data requires robust noise filtering, signal amplification, and preprocessing to ensure accurate health monitoring, increasing computational loads and storage requirements [17]. Additionally, different sensor data formats complicate the process of integrating data streams into centralized platforms, limiting timely clinical decision-making and delaying emergency responses or feedback mechanisms [18]. Recent work has explored effective strategic pathways for addressing these challenges. Interoperability between diverse data sources can be significantly improved by adopting standardized protocols such as HL7 FHIR and IEEE 11 073 [19]. Data compression techniques, like wavelet-based encoding, have shown promising results in reduced data storage and transmission scenarios while preserving data quality [20]. Moreover, data fusion strategies using DL or statistical methods help to combine multimodal data streams for unified health analytics [21]. Edge computing platforms are increasingly being deployed to process and filter data locally, thereby reducing transmission loads and enabling faster clinical decision-making. These combined approaches enhance system scalability, responsiveness, and accuracy in real-time health monitoring [16], [22].

B. Energy Consumption and Memory Complexity

In continuous e-health monitoring, wearable devices must prioritize energy efficiency and form factor to ensure comfort and long-term usability. This necessitates the use of low-power sensors; however, continuous sensing, processing, and wireless data transfer significantly affect battery life, making energy optimization a critical design concern [23]. A major tradeoff emerges between memory architecture, data transmission, and energy consumption. Compact designs restrict the inclusion of high-capacity onboard memory, requiring frequent data transmission to external nodes, which further drains power.

Commercial wearables typically include limited onboard memory modules (often in the range of a few gigabytes) to maintain device convenience and lightweight design. For example, popular wearable devices, Fitbit Watches usually incorporate minimal internal memory (typically 3GB), relying heavily on frequent data synchronization to edge or cloud platforms [24]. Notably, frequent data transmission and high sampling rates contribute significantly to battery depletion. For instance, a 10-fold increase in sampling rate may lead to a 64% rise in energy consumption, with current draw increasing from 4 to 10 mA in typical MEMS-based sensors [25]. Such increases for prolonged duration significantly shorten the operational life of wearable systems, particularly in applications requiring continuous monitoring. Conversely, integrating larger memory modules to reduce transmission frequency adds bulk, weight, and compromises wearability, which is critical since wearable convenience is typically defined by dimensions that do not significantly exceed standard wristwatch sizes [23]. Additionally, embedded memory can reduce network dependence but demands efficient power management to avoid accelerating battery depletion [20].

While optimal size and weight critically drive usability and long-term compliance, standardized thresholds are difficult to define due to the subjective and context-specific nature of wearability preferences across users and applications [26]. Therefore, wearable systems need to find a balance between local storage, transmission frequency, and power constraints. Solutions such as data compression, adaptive sampling, intermittent transmission, and hybrid edge-cloud storage architectures are increasingly employed to mitigate these limitations without compromising data quality or user comfort [20], [25], [27].

C. Real-Time Data Processing and Latency Tolerance

Continuous data processing and transmission in wearable devices significantly impact battery life, limiting device usability in energy-constrained scenarios. Real-time data processing further increases device complexity, as it requires fast, efficient algorithms and sufficient computational resources.

Latency tolerance refers to a system's ability to handle delays in data transmission or processing without compromising its intended performance or reliability. Systems with low latency tolerance, such as elderly fall-detection monitors, demand near-instantaneous processing and alerts, as even minor delays may pose serious risks to user safety [28]. Conversely, fitness trackers generally have higher latency tolerance since minor processing or transmission delays do not substantially impact user experience or pose immediate health risks. Attempting real-time processing and transmission of large continuous data streams over limited bandwidth networks can lead to network congestion, increased delays, and potential loss of critical data packets—collectively known as network "bottlenecks." These issues can degrade the overall performance of latency-sensitive IoT healthcare systems. Thus, careful system design involving adaptive data sampling, prioritized data streams, and edge-computing solutions is essential to mitigate these bottlenecks and ensure appropriate latency performance [28].

D. Data Integrity and Data Security

Data integrity in the context of e-health refers to the precision, consistency, completeness, and reliability of health data throughout its lifecycle, from initial collection through storage, processing, retrieval, and analysis. It ensures that the data remains unaltered and uncorrupted for making informed medical decisions and facilitating seamless clinical services. However, maintaining data accuracy and consistency is challenging due to continuous data streams from diverse wearable devices, each susceptible to noise, missing data, and sensor inaccuracies [29].

Current research focuses on robust preprocessing methods, such as noise filtering, anomaly detection, and data imputation techniques, to ensure data quality and integrity. For example, Van Der Donckt et al. [30] highlight several methodologies in their observational ambulatory studies, addressing data quality challenges through statistical data validation, anomaly detection algorithms, and systematic preprocessing to ensure reliable health monitoring. Moreover, wearable devices transmit data through Wi-Fi, Bluetooth, and other wireless communication technologies. The sheer volume of data transmitted over the network increases the risk of potential data breaches and unauthorized access, posing significant concerns for data security and privacy [31], requiring researchers to take more extensive measures to increase data security [32]. As healthcare systems become increasingly digitized and rely on artificial intelligence for disease detection, management, and parameter monitoring, their vulnerability to security threats also increases, posing risks to patient safety and data integrity. Poisoning attacks, where adversaries introduce malicious data into training datasets, can deteriorate model performance, resulting in misdiagnoses or incorrect treatment recommendations [33]. Similarly, adversarial attacks can manipulate real-time sensor readings, causing ML models to misinterpret significant physiological parameters [33]. Additionally, model inversion attacks pose privacy risks by extracting sensitive patient information from trained models [34].

To mitigate these threats, security measures such as robust adversarial defense mechanisms, anomaly detection systems [35], gradient sign mechanisms using differential evolution [36], secure federated learning, knowledge distillation [37], and feature enhancement [38], [39] can be integrated into IoT-driven healthcare platforms. Furthermore, postquantum cryptographic (PQC) techniques [40], including key encapsulation mechanisms (KEMs) and digital signatures [41], [42], can enhance communication security, protecting patient data from cyber threats. Addressing these security concerns is crucial for ensuring the reliability, privacy, and trustworthiness of IoT-based healthcare systems.

III. Types of Wearable Devices

A wearable device is a form of technology that can be comfortably worn on a particular part of the body, usually in the form of clothing, accessories, or implants. These devices are designed with integrated sensors, processors, and communication features that allow them to gather data, perform diverse functions, and interact with users, physicians, or other people, such as emergency contact persons. Wearable devices are one of the most convenient methods for continuously collecting health-related data from users [52]. In this section, we present a comprehensive overview of wearable devices that are commercially available, along with the results of research applications in this field. We provide a brief overview in Table I, summarizing the sensors and features of the commercially available devices, and then we discuss the academic research on wearable devices in the latter part of Section III-B and onward.

A. Hand-Worn Fitness Tracker

A wrist-worn wearable device for fitness tracking is one of the most popular kinds of wearables among health-conscious individuals [53]. This is a type of wearable technology that is specifically designed to be worn on the wrist like a watch or a bracelet. These devices typically incorporate diverse integrated sensors, such as accelerometers, heart rate monitors, gyroscopes, and GPS, enabling tracking and monitoring of various aspects of the user's physical activity and health. In this section, we discuss the commercially available fitness tracking wearable devices with four prominent options.

These devices, Fitbit, Apple Watch, Oura Ring, and Whoop, offer distinct functionalities. Fitbit's latest "Fitbit Versa 4" [24] includes a variety of sensors, providing insights into calories burned, heart rate, sleep, and stress levels. Apple Watch [44] detects irregular heart rhythms like atrial fibrillation, fall detection, and offers crucial health notifications. Oura Ring [43], worn on the finger, measures heart rate, skin temperature, respiratory rate, SpO2, and tracks sleep stages comprehensively. Whoop's 4.0 [45] version provides more precise heart rate with a PPG sensor, monitors skin temperature, oxygen saturation, and respiratory rate, and offers comprehensive sleep tracking.

B. Chest-Worn Heart Health-Monitoring Device

Cardiac health is monitored and assessed using a variety of technologies, among which electrocardiography, photoplethysmography, phonocardiography, and ballistocardiography are the primary methods that are universally employed. Electrocardiography is a specialized technique that uses electrodes designed to be worn on the user's chest skin surface for monitoring the user's heart's electrical activity [54]. Photoplethysmography is a noninvasive way of monitoring arterial pulse wave using an optical sensor [55]. The phonocardiography technique uses piezoelectric sensors, microphones to capture the sound of the heartbeat or murmurs resulting from auscultation [56]. Ballistocardiography is an excellent option for continuously monitoring cardiac health. This signal captures the reaction of blood in the form of velocity or acceleration, and displacement during a pulse in the user's body [57].

The TICKR chest strap, by "wahoo" monitors heart rate and tracks calories burned through its integrated optical sensor while transmitting real-time data [46]. The ECG sensor in the Polar H7 chest strap collects heart rate data [58], ensuring maximum accuracy with noise rejection [48]. Similarly, the Garmin HRM-Dual monitors real-time heart rate, measures heart rate variability, and transfers real-time data [47]. Due to its proximity to the heart, chest-strap-based heart rate monitors are more reliable and accurate than wrist-worn devices.

Chiarugi et al. [59] have proposed a wearable device in the form of a shirt for recording chest movement with a one-lead ECG sensor. They have developed a signal processing method for evaluating heart rate and respiratory rate, two of the critical parameters for monitoring heart health. A methodology for evaluating stroke volume in congenital heart disease patients using seismocardiogram and ECG signals from a chest-worn wearable device is proposed by Ganti et al. [60]. Button-sized chest-worn wearable for estimating heart rate from ballistocardiogram signal has also been developed [61]. An inertial measuring unit with the following sensors—gyroscope, accelerometer, and magnetometer—provides the ballistocardiogram signal, which is used to measure the mechanical movement of the user's chest during a pulse. Sanfilippo and Pettersen [62] have presented a chest-worn wearable system that collects user data for continuous health monitoring using a sensor fusion technique with an accelerometer, an ECG, and a temperature sensor.

C. Brain Wave Monitoring Using EEG

EMOTIV is a commercially available head-worn wearable device for collecting the EEG signal [63]. This device has multiple electrodes for collecting the EEG signal and additional sensors (accelerometer and magnetometer) for detecting head movement. The Project Amber is a project from Google Inc., where researchers have developed an unsupervised DL method for generating a denoised EEG signal from an EEG wearable and extracting interpretable features related to mental health [64]. A forehead-based wearable device for collecting the EEG signal is designed by Wan et al. [65] for emotion detection. This device can be mounted with a bio pad, allowing it to collect EEG and PPG signals and skin temperature data continuously. These data are then used for emotion recognition using a VR Head-Mounted Display. While head-mounted EEG devices may not be technically "continuous monitoring

TABLE I
SUMMARY OF COMMERCIALLY AVAILABLE WRIST-BASED WEARABLES

Device	Sensors	Features
Fitbit Charge 5 [24]	• Optical heart rate sensor • Accelerometer • Ambient light sensor • Multipurpose electrical sensor for EDA	• Step count • SPO2 • Heart rate • Heart rhythms • Detect atrial fibrillation • Skin temperature • Sleep monitoring • Stress tracking
Fitbit Versa 4 [24]	• Optical heart rate sensor • Accelerometer • Ambient light sensor • Altimeter • Red and infrared sensor	• Step count • Floor count • SPO2 • Heart rate • Skin temperature • Sleep monitoring • Stress tracking
Oura Ring Gen 3 [43]	• Optical heart rate sensor • Accelerometer • Red and infrared sensor • Negative temperature coefficient (NTC) sensors	• Heart rate at different conditions • Skin temperature • SPO2 • Respiratory rate • Sleep monitoring
Apple Watch Series 6 [44]	• Optical heart rate sensor • Electrical heart sensor • Accelerometer	• Heart rate • Heart rhythms • Detect atrial fibrillation • Fall detection
Whoop [45]	• Red and infrared sensor • Skin temperature sensor • PPG	• Skin temperature • SPO2 • Heart rate • Respiratory rate • Sleep monitoring
TICKR Chest Strap [46]	• Optical heart rate sensor • Accelerometer • LED	• Heart rate • Calories burned • Intuitive feedback system • Real-time wireless data transfer
Garmin HRM-Dual [47], Polar H7 [48]	• ECG sensor • Accelerometer	• Heart rate • Motion and activity level tracking • Real-time wireless data transfer
Oxxiom [49]	• Red and infrared LED • Photodetector	• Oxygen saturation • Pulse rate • Perfusion index
DexCom G6 [50]	• Dexcom G6 Sensor	• Monitors glucose level • Fingerstick free device • Real-time data transmission
K5 Metabolic System [51]	• Gas filter correlation(GFC) sensor • Nondispersive Infrared(NDIR) sensor	• Respiratory gas response • Metabolic rate

devices" in the sense that they may not be suitable for continuous, round-the-clock use, they are included since they are well-suited for wearing for a limited duration to gather the required continuous data.

D. FDA-Cleared Wearable Device

Healthcare equipment is considered suitable for the consumer market if it obtains official clearance from the Food and Drug Administration (FDA), supporting its compliance with essential criteria for safety, quality, and appropriateness. Below, we provide a few examples of companies and healthcare devices that have successfully obtained FDA clearance [66] in recent years.

1) *Oxxiom*: This pulse oximeter, by 'True Wearables,' offers noninvasive measurements of arterial oxygen saturation, perfusion index, and pulse rate [49].

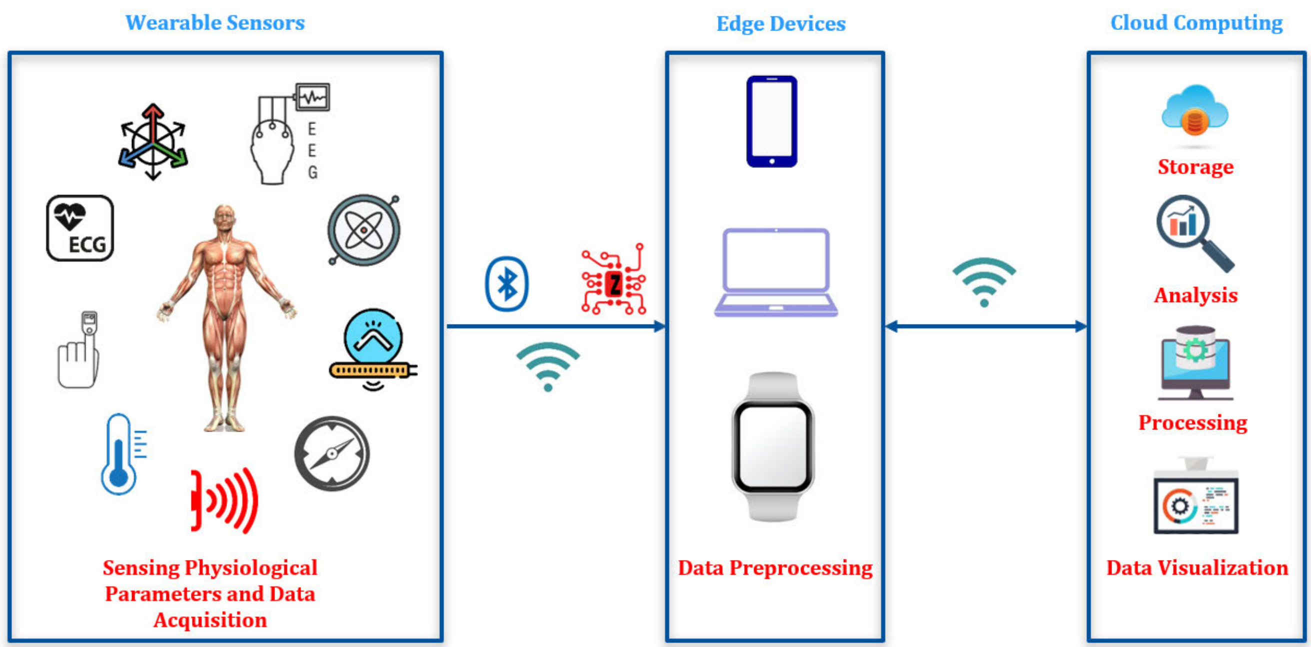

Fig. 3. Basic system architecture of a current IoT healthcare system.

2) *Philips Biosensor BX100*: This device manages COVID-19 patients in hospitals, monitoring critical early indicators crucial for infected patients, namely respiratory rate and heart rate [67].
3) *DexCom G6*: This is an abdomen-worn continuous glucose-monitoring device with real-time data transfer leading to improved outcomes like lower A1C test results and reduced hyper- or hypoglycemia incidents [50].
4) *K5 Wearable Metabolic System*: COSMED k5 measures respiratory gas responses with two distinct modes: microdynamic mixing chamber and breath-by-breath techniques [68] showing high precision, particularly in low-intensity exercise, in the breath-by-breath mode [69].
5) *Zio Patch*: Zio patch by "iRhythm" continuously records user's ECG signal. The continuous real-time data offers efficient diagnosis and treatment for irregular heart rhythms [70]. Extended monitoring capability allows it to detect arrhythmia more precisely than other devices [71].

E. Other Waist/Chest-Worn Wearable Devices

A low-power computational methodology for monitoring real-time physical activity and measuring energy expenditure during exercise or various physical activities using a shoe-based wearable device coupled with a smartphone is proposed by Sazomov et al. [72]. Mobile sensing platform (MSP) is a project by Intel where a lightweight waist-worn device is developed to identify various physical activities such as walking, climbing stairs, cooking, and sitting. This wearable employs a semi-supervised ML approach to automatically classify these activities based on data from an integrated accelerometer and microphone [73]. Vieira et al. [74] have introduced an ML method to evaluate the severity of amyotrophic lateral sclerosis (ALS) as well as to track the advancement of the disease and the efficiency of the medicine "edaravone" in treating ALS patients. This model is developed using the speech samples collected from the user's mobile phone and accelerometer data obtained from a limb-worn wearable device. A smart glove for measuring the range of motion of arthritis patients by detecting joint movements has been developed by O'Flynn et al. [75]. The device consists of stretchable and flexible materials, allowing users to move their fingers conveniently. The device measures each finger's degree of freedom using the IMU's sensor data.

IV. Technological Approaches

The enabling technologies play an important role in successfully developing convenient, user-friendly, and low-power wearable devices suitable for continuous health monitoring. Fig. 3 shows the basic system architecture employed in current research in the field of continuous health monitoring. In this section, we will discuss the most important technologies that are widely employed in e-health for continuous monitoring.

A. Sensor Technology

Sensor technology has evolved significantly over the past decade, transitioning from bulky, power-intensive modules to compact, low-power microelectromechanical systems (MEMSs). Early wearable devices primarily relied on basic motion sensors, but recent innovations have led to integrated platforms featuring accelerometers, gyroscopes, magnetometers, and physiological sensors. These advancements in small-scale MEMS devices have enabled sophisticated, multi-parametric monitoring in compact devices [76].

Inertial sensors (accelerometers and gyroscopes) can detect movement, posture, and activity intensity with high accuracy

TABLE II
COMPARISON OF COMMUNICATION PROTOCOLS USED IN WEARABLE AND IOT-BASED HEALTHCARE SYSTEMS

Comparison Metric	ZigBee	Bluetooth	Wi-Fi	6LoWPAN
Operation Range	Short	Short	Medium	Medium
Data Rate	250 Kbps	Up to 1 Mbps	Up to 600 Mbps	250 Kbps
Power Usage	Very Low	Low	High	Very Low
Number of Nodes	Up to 65,000	Up to 8	10–25 (802.11) / Up to 8,191 (802.11ah)	Hundreds to Thousands
Data Format	Structured sensor data	Rich (text, multimedia)	Rich (files, media)	IPv6 Packets / Compressed Data
Use Case	Multi-sensor health networks	Personal health tracking	Bulk data upload	Scalable IoT health systems

due to their robustness. The low power consumption property makes these sensors ideal for wearable device integrations, especially for tasks such as fitness tracking and sleep monitoring, and so on. However, they lack physiological specificity and are prone to motion artifacts in clinical contexts [24], [44]. Physiological sensors, such as the electrocardiogram (ECG), photoplethysmogram (PPG), galvanic skin response (GSR), and skin temperature sensors, offer direct insights into vital functions but often require complex signal preprocessing and calibration, sometimes leading to higher energy demands [77]. Comparative studies show that, for fitness applications, MEMS-based inertial sensors are the preferred choice due to their low power consumption property, while for clinical-grade health monitoring, predictive analysis of disease status or getting a detailed overview of a specific parameter/vital, physiological sensors provide higher diagnostic value when combined with robust signal-processing pipelines [78], [79].

Ultimately, selecting the appropriate sensor depends on application context: low-power motion tracking for fitness, versus high-precision physiological tracking for clinical monitoring. Future research can focus on hybrid sensor design, adaptive sampling, and efficient edge processing to bridge the gap between consumer-grade wearables and clinical accuracy.

B. Communication

The body-worn sensors in the wearable devices collect a variety of physiological information indicating the patient's vitals, such as body temperature, ECG/EEG signal, blood pressure trending, body glucose level, and other key indicators. Once data acquisition is completed successfully, these sensors transmit the data to the coordinating node for temporary storage. The coordinating node has more data storage capacity, continues to collect data from the sensor, and transmits high-volume data to remote healthcare centers or the cloud server of smart healthcare services for further analysis. For efficient monitoring and diagnosis, communication between components of smart healthcare services must be reliable, uninterrupted, and sustainable.

Short-range wireless protocols such as Bluetooth Low Energy (BLE) and ZigBee are commonly used in wearable healthcare systems for transmitting sensor data to nearby coordinator nodes. BLE operates globally at 2.4 GHz, supports diverse data formats—including text, sensor readings, and multimedia (audio/video)—making it ideal for personal health tracking. In contrast, ZigBee operates at region-specific frequencies and transmits structured, low-bandwidth physiological data. ZigBee supports up to 65 000 nodes, unlike BLE's limit of 8 nodes, making it well-suited for multisensor clinical environments. ZigBee also offers self-healing capabilities, where neighboring nodes are able to reroute data if one fails, enhancing network resilience. Though ZigBee has a lower data rate (250 Kbps) than BLE (1 Mbps), it is more energy efficient and stable in large networks [80], [81].

Medium-range protocols like Wi-Fi and 6LoWPAN enable communication between coordinator nodes and remote servers or cloud platforms. Wi-Fi, with high throughput and device compatibility, is better suited for intermittent, high-volume data transfers, but it consumes more power, making it less ideal for battery-dependent wearables [82]. On the other hand, 6LoWPAN supports low-power communication, packet compression, and scalability, making it a strong candidate for resource-constrained e-health systems that require stable, low-bandwidth connectivity [83].

Table II shows a summarized information of these protocols over a few comparison metrics [80], [81], [82], [83], [84], [85]. BLE is best suited for individual, low-power wearables requiring smartphone connectivity and rich data formats. ZigBee is preferred in scalable, low-bandwidth sensor networks, especially for long-term physiological monitoring in clinical or home settings. Wi-Fi is ideal for bulk data uploads where power is less constrained, while 6LoWPAN fits low-power, distributed IoT networks where efficient packet transmission is essential.

C. Data Processing, Analyzing, and Diagnosis Using ML and DL Methods

Evaluating health status, detecting disease severity, early disease diagnosis, or chronic disease management by manually reviewing high-volume patient data is not feasible for healthcare professionals or clinicians. This heavy computational work has never been easier than now it is with the availability of various computational models. The evolution of data-driven approaches in healthcare has shifted from traditional ML models to more complex DL architectures, driven by the exponential growth in physiological data collected from wearable IoT devices. Initially, time-series models like moving average models (ARIMA) and classic classifiers like SVMs and decision trees were employed to analyze structured health data and detect physiological anomalies [86], [87]. Over time, DL models such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have emerged, enabling advanced signal interpretation from raw biosignals like ECG, PPG, and so on [77], [88].

A key comparison during model selection lies in the trade-off between computational complexity and data adaptability.

TABLE III
COMPARISON OF ML AND DL MODELS IN HEALTHCARE

Aspect	Machine Learning (ML)	Deep Learning (DL)
Data Requirement	Moderate-sized, only handles structured data	Large-scale, handles unstructured data
Model Complexity	Simple to moderate	High
Interpretability	High	Low (black-box models)
Computational Cost	Low to moderate	High (needs GPUs/TPUs)
Edge Deployment	More feasible	Limited (unless optimized)
Use Case	Early detection, real-time feedback system	Complex pattern recognition, signal/image analysis

TABLE IV
COMPARISON OF EDGE AND CLOUD COMPUTING IN IOT-BASED HEALTHCARE

Aspect	Edge Computing	Cloud Computing
Processing Location	Near the device (local)	Centralized (remote servers)
Latency	Low	Moderate to high
Real-time Support	High	Depends on connectivity
Scalability	Limited	Virtually unlimited
Power Consumption	Device-dependent	Offloaded from device
Security/Privacy	Higher (local data retention)	Riskier (centralized exposure)
Use Case	Real-time alerts, low-latency response	Historical analysis, heavy ML inference

Traditional ML models are computationally lightweight and perform well on structured datasets, making them ideal for edge-device deployment. For example, SVMs and logistic regression models are effectively used to estimate posture and calculate energy expenditure from multiple force-sensitive resistors (pressure sensors) and accelerometer data, offering fast computation in a wearable setting [72]. In contrast, DL models such as those used by Yen et al. [77] for signal-processing tasks, such as estimating blood pressure and heart rate, provide improved accuracy and generalizability but require greater computational power and training data.

The strength of ML models lies in their interpretability and efficiency for smaller or well-structured datasets. They are particularly effective in early diagnosis tasks, such as Alzheimer's prediction using SVMs and boosting techniques on neuroimaging data [86]. However, the basic ML models may struggle with unstructured signals or noisy inputs. DL models, while less interpretable and more computationally intensive, are capable of extracting deep features from complex signals or unstructured data, such as audio, or digital phenotyping of progressive diseases [74].

Model selection should align with the application context. Lightweight ML models are better suited for edge-based, real-time detection with constrained processing capabilities, as demonstrated in COVID-19 risk prediction using respiratory rate trends [89]. On the other hand, DL models are ideal for centralized platforms, which allow for high-accuracy detection of complex events, such as in passive, explainable ALS severity estimation using multimodal inputs [74].

Ultimately, both ML and DL methods play complementary roles in advancing health-monitoring systems. As summarized in Table III, these models differ in terms of data requirements, complexity, interpretability, and suitability for edge deployment. While DL offers superior performance in handling complex data, ML remains favorable for its simplicity and feasibility on resource-constrained devices. Therefore, their application needs to be carefully balanced based on their tradeoffs between accuracy, interpretability, and computational efficiency. Looking ahead, future research can explore hybrid and explainable models that leverage the strengths of both approaches, ensuring scalable, precise, and interpretable diagnostics in real-world wearable healthcare systems.

D. Cloud/Edge Computing

Computation in healthcare has evolved significantly, transitioning data processing from local, device-based methods to centralized servers. Early wearable devices perform basic local processing, limited by storage, computational power, and battery constraints. Modern advancements in high-speed communication now facilitate cloud-based analytics, allowing resource-intensive DL and big-data analyses to run efficiently without burdening the device itself [90].

The key tradeoff between cloud/edge computing involves balancing wearable compactness and power efficiency against processing capability. Device-based computation enables faster response and improved data privacy, but is constrained by limited resources. Cloud computing, on the other hand, offers superior scalability, virtually unlimited processing power, and extensive data storage, enabling sophisticated ML analyses. However, it relies heavily on consistent network connectivity and may introduce latency and security vulnerabilities. Fog computing, a hybrid approach, distributes processing between devices and the cloud to reduce latency and improve security [91]. A comparative overview of these computing paradigms, cloud and edge, is summarized in Table IV, highlighting their relative advantages across key aspects such as latency, scalability, and privacy. The choice between edge, fog, and cloud computing depends largely on specific application requirements. Cloud computing is preferred for computationally intensive tasks, large datasets, and complex historical analyses. Fog computing is better suited for low-latency applications requiring rapid responses and enhanced security. Edge computing is better suited for tasks that require rapid response and high data privacy. Ultimately, hybrid cloud–edge architectures hold the most promise, combining strengths from both models to optimize wearable healthcare solutions' performance and user-centric design [92].

V. Current Health-Monitoring Research

A. Disease Detection

1) Infectious Disease Detection: Continuous monitoring of unusual patterns in physiological parameters, such as body temperature, respiratory rate, and oxygen saturation, can significantly improve early detection of diverse respiratory infections. Traditional procedures are inconvenient for real-time monitoring, motivating the development of wearable technologies that can track anomalies in vitals through continuous monitoring.

Huan et al. [18] have developed a template-matching algorithm to detect deviations in body temperature via wrist-worn sensors, while Ota et al. [93] have developed a smart earbud for monitoring tympanic temperature through an infrared sensor. Boonsong et al. [94] introduced a wireless infrared (IR) system for contactless body temperature monitoring. A device to measure respiratory rate from the air volume during a spirometry test was developed by Larson et al. [95]. Mahbub et al. [96] have designed a low-power chest-worn wearable device using a piezoelectric sensor for monitoring patients' respiratory rate with wireless data transfer capability. Fu and Liu [97] have developed a wrist-worn noninvasive wearable device using near-infrared (NIR) spectroscopy technology for measuring sportsmen's oxygen saturation. The NIR technology measures oxygen level fluctuations in hemoglobin present in small blood vessels. Xie et al. [98] have developed an IoT-based pulse oximeter with real-time data-monitoring capabilities. This device is designed to detect the user's blood oxygen saturation, along with additional physiological data, including the perfusion index and pulse rate.

COVID-19 Case Study: The COVID-19 pandemic highlighted one of the most complicated healthcare concerns of the twenty-first century across the globe. It also caused a rapid growth in healthcare research, including (but not limited to) the application of IoT technology in remote care, monitoring, and disease detection. Gadaleta et al. [87] proposed an adaptable algorithm that combines self-reported patient data with sensor data for predicting COVID-19 infection. While this algorithm can adapt to missing survey data, self-reported data are crucial for an accurate result of COVID-19 detection in symptomatic patients. Natarajan et al. [99] developed a CNN model for predicting COVID-19 infection based on the respiratory rate (RR), heart rate (HR), and heart rate variability (HRV) data collected from a Fitbit device [24]. The trained model analyzes the most recent five days of health data and predicts infection with an accuracy from 12% to 43%.

Miller et al. [89] have evaluated the viability of using abnormal respiratory patterns as an indicator of COVID-19 infection. The respiratory rate (RR), resting heart rate (RHR), and heart rate variability (HRV) data, along with self-reported symptoms collected from WHOOP [45], are used to develop the method for estimating COVID-19 infection probability based on changes in the pattern of the mentioned physiological parameters. Mason et al. [100] have developed an algorithm for detecting COVID-19 onset using the sensor data (HR, RR, skin temperature, and physical activity) collected from the OURA ring [43], and self-reported symptoms.

These wearable-based COVID detection methods require patients' self-reported symptoms for achieving higher accuracy. However, a methodology for predicting infectious respiratory disease through continuous vitals monitoring in symptomatic patients without requiring self-reported symptoms has been developed by Mila et al. [101]. They use various physiological data such as body temperature, respiratory rate, oxygen saturation, heart rate blood pressure to train a DL model for finding patterns in symptomatic patients. The concept of utilizing advanced ML methods to predict the state of infectious diseases through continuous vitals monitoring represents a novel advancement.

2) Chronic Disease Detection: Chronic diseases are defined as conditions that persist over an extended duration, typically advance gradually, require continuous medical observation, and have the ability to restrict a person's regular activity [102].

Hypertension, commonly referred to as high blood pressure (BP), is a chronic condition that, if not appropriately managed, can result in heart disease and stroke. The mortality rate associated with CV disease or stroke can be significantly lowered if hypertension can be detected and treated early. Chest-worn wearable devices for continuous BP monitoring are available [79]. An information therapy-based telemedicine model is developed using a multiagent communication structure involving health technicians, agents, and clinical experts, where the patient's blood pressure is monitored and maintained regularly [103]. An IoT-based location-intelligent terminal for portable BP monitoring is developed and proposed in [104]. A cuffless wearable device with photosensors for errorless, high precision, and continuous BP monitoring is developed [105]. A device for predicting hypotension due to postural change has also been developed [106]. Early detection and management of orthostatic hypotension are also crucial since untreated hypotension can lead to multiorgan failure, loss of consciousness, concussion, and coma in severe cases.

Diabetes is a chronic condition characterized by prolonged elevated levels of blood glucose. A noninvasive technique for continuous glucose level monitoring is proposed by Istepanian et al. [107]. Alert-based systems for notifying healthcare experts of critical cases, such as a sudden drop or rise in glucose level, can be more helpful in addition to regular blood glucose-monitoring systems [108].

Kavitha et al. [86] have developed an ML methodology for detecting the stage and severity of Alzheimer's disease. PredictAD is a software tool that models a patient's disease state by analyzing available heterogeneous data and extracting relevant features, which helps in diagnosing the disease at an early stage when it is still possible to manage it [109].

3) CV Disease Detection: The mortality rate due to CV disease is notably substantial [110]. Early detection of unusual patterns in heart rate can allow patients to have an early diagnosis of CV disease, preventing it from progressing and lowering the number of deaths caused by the advanced stage of CV disease. Continuous heart rate-monitoring technology plays a significant role in detecting unusual heart rate patterns. He et al. [111] have proposed a wireless earbud for continuous heart rate monitoring. This device measures the ballistocardiographic movement of the user's head using an

MEMS accelerometer. This electrodeless wearable makes it more convenient for continuous use. A contactless system for continuous heart rate monitoring using the ballistocardiographic data is developed by Sumali et al. [112]. This system employs custom-made load-cell sensors installed into the legs of a chair, where the sensors detect subtle vibrations caused by the user's heartbeat. This system measures heart rate data more accurately than the conventional methods. An ML method for continuous measurement of stroke volume using a noninvasive chest-worn wearable device is proposed by Ganti et al. [60]. The ridge regression analysis algorithm can handle multicollinearity, which makes it stand out from other algorithms for the task of estimating stroke volume. The combination of cardiomechanical features from the seismocardiogram signal and electrical features of the ECG signal allows the device to monitor stroke volume conveniently and continuously. An IoT-based noninvasive system for continuous heart rate monitoring using a photoplethysmographic sensor [113], and a single lead electrode [114] is also developed.

B. Continuous Health Monitoring for Analysis

1) Ambient Assisted Living: Ambient assisted living (AAL) is a system that places smart gadgets and sensors in the surrounding environment to offer assistance and care to people. AAL is useful for elderly people or patients who suffer from chronic diseases and require continuous health monitoring to reduce their dependency on caretakers or healthcare experts. Availability of AAL techniques has allowed people with impairments to stay in their homes with continuous availability of the required healthcare advice and has lowered their medical expenses. Rafferty et al. [115] have presented a personal IADL assistant system that offers assistive living to elderly people by helping them in performing daily activities independently. PIA uses inexpensive and easy-to-use near field communication (NFC) tags attached to household objects and instructional videos on their usage. It helps elderly people to use their household smart devices without requiring any external help.

An IoT-based telemonitoring system incorporating RFID and NFC technology is proposed by Dohr et al. [116]. A combination of closed-loop healthcare services and keep-in-touch (KIT) technology allows user to establish easy and efficient communication with their physician, in addition to relevant health data acquisition. An ontology-driven monitoring system for AAL is developed by Bampi et al. [117], which integrates IoT-based smart home models with SNOMED CT-like clinical terminologies to allow easy interoperability and context-aware reasoning. The proposed system employs semantic web rule language (SWRL) rules, offering features like real-time, patient-specific alerts. The system's viability is demonstrated through evaluation in a smart home testbed. Gingras et al. [118] have proposed a four-layer modular architecture offering health analytics and assistive living to elderly people. They have developed an automated decision-making methodology for selecting the most appropriate algorithm for a particular task and analyzed its feasibility through a user study. Hou et al. [119] proposed a wearable system for continuous health and fall monitoring. The system is designed as a compact device capable of collecting multiphysiological signals in real-time, including vitals, and fall detection through a three-axis accelerometer. The design includes a smart module that supports remote data transfer and emergency alerts. This platform also supports personalized health tracking, trend analysis, and real-time guidance through a cloud-based interface, making it a promising low-cost solution for ubiquitous telehealth surveillance, especially for aging populations and chronic care scenarios.

2) Fitness Tracking: Fitness tracking refers to the system of physical activity monitoring, including identifying specific physical activity, calories burned during an exercise or workout, number of steps or floors walked in a day, and so on [120]. Fitness tracking devices are commercially available for physical activity monitoring and real-time data storage. Recent studies actively explore the scope of continuous physical activity monitoring. Wrist-worn wearable devices for real-time physical activity monitoring by identifying a specific form of activity are presented in [72] and [73]. Apple and Fitbit have commercially launched various versions of their smart watches for fitness tracking with extra features, such as real-time heart rate and oxygen saturation monitoring, sleep management, and total burned calories [24], [44]. Naranjo-Hernández et al. [121] have designed and implemented a low-cost wearable device for physical activity monitoring using an accelerometer sensor. The authors provide three different methodologies for monitoring physical activity that can be used on the same device. A wearable device for real-time activity detection in patients with obstructive pulmonary disease has also been developed [122].

3) Mental Health: Chronic stress results in various irreversible diseases, such as depression, CV disease, anxiety disorder, and so on. Hence, a continuous stress-monitoring system is required for improved mental health. Schmidt et al. [123] presented a benchmarking dataset, WESAD, compatible with wearable devices for stress detection. Koldijk et al. [124] presented a dataset containing information on the effect of stress in the working environment. The dataset contains both preprocessed and feature-extracted data in addition to the raw data. Ghosh et al. [88] have developed a DL-based methodology for detecting mental stress by converting multivariate time series data into an image. The authors have performed a feasibility analysis of the proposed methodology and have achieved an accuracy of over 94% on both previously mentioned benchmarking datasets. An ML-based activity-aware stress detection model using wearable sensors, including an accelerometer, an ECG, and a galvanic skin response sensor, is proposed by Sun et al. [125]. The model is able to classify stress with an accuracy of 92.4%.

Sleep quality and duration are directly associated with the psychological well-being of a person [126]. Current fitness tracker devices have started to incorporate sleep-monitoring technology in their designs. These devices are capable of providing a comprehensive overview of users' sleep data, including sleep stages, duration of these sleep stages, and quality [24], [43], [45]. Fitbit offers a stress scoring mechanism based on the user's sleep data, heart rate, and exercise duration [24]. Whoop also calculates the optimal sleep duration required for an individual [45]. Sleep apnea refers to a state where an individual's upper respiratory airway becomes obstructed during sleep, resulting in disrupted breathing patterns and a subsequent impact on the overall quality of sleep [127]. A low-cost and simple positive airway pressure therapy device combined with a continuous heart rate-monitoring feature has been developed by Gardner et al. [128]. The authors have integrated heart rate-monitoring capabilities by incorporating a gyroscope into a PAP mask. This approach not only addresses patients' obstructive sleep apnea but also enables the continuous monitoring of heart rate. Trigeminal nerve simulation is a therapeutic approach where the branches of the trigeminal nerve are stimulated using mild electrical signals. This stimulation regulates the activity of specific brain regions. This modulation method is used to treat attention-deficit/hyperactivity disorder in children and has been proved beneficial [129].

VI. Conclusion

The integration of IoT technology has revolutionized the healthcare system, particularly in addressing the pressing challenges posed by the continuous increase in global population and the rise of infectious and chronic diseases worldwide. Through the advancement of e-health systems, IoT technologies have played a pivotal role in meeting the demands of cost-effective and user-friendly health-monitoring solutions, thereby making a substantial impact on the healthcare system. Despite these advancements, security remains a critical concern in continuous health monitoring. Future research can explore integrating threshold-based risk assessment frameworks, such as Raccoon [130], to enhance security and reliability in IoT-driven healthcare systems. Raccoon operates on a threshold-based risk evaluation principle, systematically assessing security threats in AI-driven applications. Its integration can strengthen data integrity, enhance real-time threat detection, and secure device communication, making it a valuable addition to IoT-based continuous monitoring. Implementing such security frameworks can help mitigate adversarial attacks, protect patient data, and ensure the robustness of wearable healthcare technologies in real-world deployments. In this article, we discuss the necessity of continuous health monitoring in improving patients' health conditions and quality of life. We discuss the challenges associated with the development of continuous monitoring technology outside of a healthcare facility. We also present a comprehensive overview of various types of wearable devices for continuous health monitoring, the enabling technologies for the development of such devices, and their application in various sectors of healthcare, such as diagnosis, monitoring, prevention, and management. While this review provides a broad perspective on IoT-based continuous health monitoring, certain limitations remain. The discussion primarily focuses on existing technologies and challenges, and further research is needed to explore the long-term clinical effectiveness and large-scale deployment of wearable monitoring systems. Additionally, security concerns, particularly in real-time data protection and postquantum cryptography integration, require more extensive analysis. We hope that the comprehensive overview of the role of wearable devices in continuous monitoring will pave the way for a better understanding of the state-of-the-art in the research area and facilitate future research.

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