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SURVEY

The Internet of Things for Applications in Wearable Technology

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ABSTRACT The advent of the Internet of Things (IoT) era has propelled the development of wearable technology. Wearable devices are widely used in medical, healthcare, sports, and safety applications, bringing more convenience to the living environment. Wearable devices can be worn on the body, collect body data using sensors, and process the collected data to obtain valuable information. IoT enables devices to connect and exchange and transmit data. Wearable devices in IoT can collect data for analysis and automatically adjust wearable device functions by connecting the obtained information to other devices. In this paper, we collect and organize articles on wearable devices used in IoT from 2017 to 2022 in terms of their applications, advantages, and disadvantages. We evaluate articles to identify wearable device application areas and evaluation criteria. Finally, we discussed the open issues of wearable devices and clarified how to face the future development and efforts of wearable devices in IoT.

INDEX TERMS Internet of Things, medical, healthcare, sports, machine learning, wearable technology.

I. INTRODUCTION

Over the past ten years, consumer involvement with technology and artificial intelligence has grown significantly. Consumers' adoption of wearable technology is a component of this modern technological revolution [44]. The advent of the IoT era, advancements in low-power mobile networks, low-cost electronics, and reductions in sensor size have driven the development of wearable technology. Wearables use sensors and software that enable data interchange, communication, and real-time information access to assist users in achieving a state of self-connection. Wearable technology is, therefore, a significant portion of the IoT. [49]. IoT-enabled wearable devices can not only be attached to external accessories of various sizes, such as glasses, watches, clothes, and belts. But can even be implanted in the body or tattooed on the skin. According to an IDC report, global shipments of wearable devices grew by 9.9% in the third quarter of 2021 [1]. Additionally, empirical data shows that wearable technology is thriving in consumer markets and gaining traction in the commercial sector [41], [42]. Wearable IoT technology has been widely used in various applications, such as healthcare, security, location tracking, wellness, fitness, sports, gaming, and fashion [43]. In addition to being able to connect to the Internet, they can automatically detect, collect, transmit, and receive information via sensors while in motion or even while sleeping. They can also combine artificial intelligence or machine learning to analyze the collected data deeply, optimize human life, improve the quality of life, and help users prevent danger.

Rashid et al. [31] proposed a compact L-slot-based microstrip patch antenna that is compact, lightweight, and easy to interface with other radio frequency (RF) circuits. They performed detailed specific absorption rate simulations to measure high-frequency electromagnetic radiation effects, and the results showed that the suggested wearable device could be safely used in wearable devices in any medical field.

Ghorbel et al. [32] developed a cloud-based smart wheelchair to assist people with disabilities, which allows users to control the wheelchair through a mobile application

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such as Android. Through sensors in the wheelchair, guardians and medical staff can also monitor patients remotely.

Rehabilitation for stroke patients is often uninteresting and painful, and patients are often unable to adhere to daily rehabilitation, which can lead to decreased physical function. Agyeman et al. [33] designed an IoT-enabled wearable device for patients with upper or lower-extremity disabilities paired with a game. They alleviated the pain of patient rehabilitation while monitoring their health and rehabilitation progress remotely.

Wearable healthcare technology is an extension of wearables and has the potential to provide a practical solution to the rising need for devices to support and help the elderly [48]. Reducing the risk of medical complications in patients with chronic diseases has always been one of the challenges in the medical field. Portable medical devices and the IoT can enhance mental health, promote a healthy lifestyle, lower hospitalization and death rates, inform caregivers and medical professionals about illnesses, and help with emergency management [50]. The advent of the IoT and advances in wearable device technology will hopefully dramatically reduce the chance of acute complications. Therefore, we mainly collected relevant literature on wearable devices that can support the IoT in health monitoring, sports, rehabilitation, and improving safety. In this paper, we conducted a comprehensive survey of IoT-enabled wearables and categorized them by application areas, such as medical, sports and healthcare, safety, etc. Also, we explored the opportunities, challenges, and future research directions of wearable devices by collecting relevant research work.

The primary contributions of this paper are as follows:

- Introducing a taxonomy for wearable IoT devices.
- Discussing and analyzing methods, models, and evaluation metrics for wearable IoT devices.
- Exploring the challenges and open issues of wearable IoT devices.

The rest of this paper is organized as follows. In Section 2, we present related work to wearable devices. Section 3 describes the process of systematic literature review. Section 4 categorizes wearable IoT devices and outlines their ideas, models/algorithms, pros, cons, evaluation criteria, and datasets. Section 5 provides a statistical review and analysis of the wearable IoT research. Finally, Section 6 concludes our work.

II. RELATED WORK

Bluetooth Low Energy (BLE) is one of the most extensively utilized communication technologies for IoT-enabled wearables. BLE is used widely in industries with high privacy threats, such as healthcare, data smuggling, regular power consumption of equipment batteries, and so on, and is used by billions of devices. Barua et al. [2] classified BLE security and privacy issues in 2022. They described potential attacks for various vulnerabilities, categorized them by severity, and provided mitigation advice.

Dean et al. [3] surveyed the wearable IoT field in 2020, divided wearable devices into four categories: sports, tracking and positioning, healthcare, daily activities, and security, and explored related opportunities and challenges. They also discussed the application of the Cellular Internet of Things (CIoT) in smart wearables, which can connect IoT devices using existing mobile networks. They believe that CIoT will likely become the most widely used technology for wearable devices in the future due to the reduced cost of implementing cellular technology improvements and the advent of the 5G era.

Pollution of the environment is one of the world's most significant concerns. A wearable environmental monitoring system has been created to monitor the environment's quality continuously. Yuce et al. [4] proposed a review that wearable environmental monitoring systems can be used to monitor the fine-grained spatiotemporal distribution of pollution in a micro-environment. With wearable environmental monitoring systems, it is easier to improve environmental problems.

Wearables have many applications in various fields to improve life tasks. After the main task has been solved, focus on improving the essential performance of the wearable device. Qaim et al. [5] proposed that one of the most in-demand performance improvements is in wearable devices that use electricity. The energy efficiency of the wearable device must also be considered so that it can be worn for an extended period. Wearable devices with strong battery life can complete tasks well all the time.

The massive and fast-spreading COVID-19 started in 2019, affecting the lives of all people in the world. The rapid infectivity of the virus makes it necessary to maintain a certain distance between people. To be able to fight the virus, there are many innovative wearable devices. De Fazio et al. [6] propose a survey of applications for remote monitoring of infected patients, tracing contacts with infected people, and breaking the chain of infection. Using a wearable device to deal with virus-related affairs has significantly reduced the risk for people.

Ferreira et al. [45] discuss the prevalent developments and topics in the research on wearable technology. They determined the following five issues: i) Wearable technology consumer behavior, ii) Wearable computing and big data analytics, iii) Wearable computing decision-making; iv) Wearable computing utility; and v) Wearable technology well-being. Moreover, they identify essential issues that could guide future research on wearable computing and customer engagement.

With a survey analysis of AO Trauma members, Braun et al. [46] examine the current usage of wearable technology by trauma surgeons, identify surgeon requirements in this area, and assess the currently perceived barriers that impede a larger deployment in the clinical situation.

Almusawi et al. [47] examined many areas of focus for technical and educational research. The review summarizes the research theories, methodologies, categories of wearable technology, applications, and contributions to the field of

TABLE 1. Comparison of the related surveys in IoT-based wearable devices.

Reference	Main Topic	Publication year	Covered years	Taxonomy	Open issues and future directions	Analyzed applications	Benefit	Drawback
Barua et al. [2]	Bluetooth Low Energy in IoT-based wearable	2022	1994-2022	Presented	Presented	Applications for Bluetooth Low Energy	Attacks on BLE are classified. Introduction and analysis of BLE.	Focus on BLE security, no discussion of wearable device applications
Dian et al. [3]	IoT-based wearable applications	2020	2004-2020	Presented	Presented	• Health • Activity • Tracking • Safety	Discussing applications in different fields	Not all applications are compared
Al Mamun et al. [4]	Environmental monitoring in IoT-based wearable	2019	1992-2019	Presented	Presented	Applications for wearable environmental monitoring Systems	Discussing target parameters for WEMS	Only the application of environmental monitoring systems is discussed.
Qaim et al. [5]	Energy efficiency in IoT-based wearable	2020	2005-2020	Presented	Presented	• Healthcare • Activity recognition • Smart environments • General solutions.	Statistical analysis of the energy efficiency field of wearable devices	Focus only on energy efficiency issues
De Fazio et al. [6]	Symptom detection in IoT-based wearable	2021	2005-2021	Not Presented	Presented	Applications for fighting the COVID-19 pandemic	Exploring several commercial wearable technology options	Only covers wearables for covid-19
Ferreira et al. [45]	Wearable technology and consumer interaction	2021	2002-2021	Not Presented	Presented	-	Identify key issues in wearables and consumer interaction research.	Less description of wearable technology
Braun et al. [46]	Wearable technology in orthopedic trauma surgery	2022	2001-2021	Not Presented	Presented	Applications for orthopedic trauma surgery	Promoting the development of low-cost wearables for orthopedic surgery	Only covers wearables for orthopedic trauma surgery
Almusawi et al. [47]	Wearable technology in the education field	2021	1999-2019	Not Presented	Presented	Applications for education	Explore the ethical, legal, economic, innovation, privacy, and other aspects of knowledge-based wearables.	It only covers wearables for education

education. Then, it discusses the theoretical underpinnings and outlines the route that future research should take.

Table 1 compares the related survey papers on the IoT-based wearable devices issues in terms of presented taxonomy and open issues, analyzed applications, benefits, and drawbacks of each survey.

As evidenced by the available literature, several survey papers either focused on a particular application domain or considered only a small portion of wearable devices. Also, some review papers do not systematically conduct their literature reviews. In addition, some survey papers lacked a taxonomy. Nevertheless, in this paper, in addition to presenting a significant taxonomy, and collecting literature on wearables that can support IoT in health monitoring, exercise, rehabilitation, medical, sports, and safety, we have systematically reviewed the most comprehensive application of IoT-based wearable devices to overcome the limitations mentioned above.

III. RESEARCH SELECTION METHOD

This article reviews 8 IoT-based wearable device surveys [2], [6], [45], [47]. In addition, we also collected 36 studies on wearable devices applied in medical, healthcare, and other fields [7], [32], [50], [55]. By combining alternatives and synonyms for keywords, the following search terms are defined:

☐ To find five survey papers, we used the following search terms:

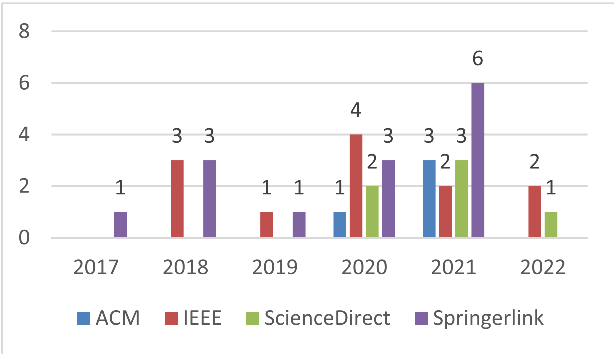

FIGURE 1. Research article distribution per publication.

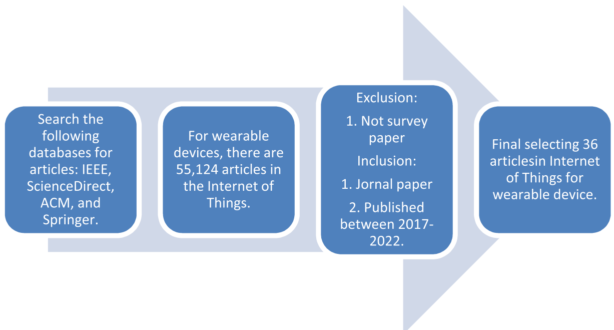

FIGURE 2. The selection process of studies.

("Wearable" OR "Wearable device") AND ("Internet of Things" OR "IoT") AND ("Survey")

☐ To find 30 research papers, we used the following search terms:

("Wearable" OR "Wearable device") AND ("Internet of Things" OR "IoT") AND ("Health" OR "Wireless" OR "Safety" OR "Medical")

This paper presents inclusive answers to the following Research Questions (RQs) regarding the aims of this research:

☐ **RQ1: What is the number of publications over time?**

☐ **RQ2: What are the elevation factors used in wearable IoT?**

☐ **RQ3: What are applied algorithms/methods in wearable IoT?**

☐ **RQ4: What are the challenges and open issues in wearable IoT?**

Figure 1 depicts the distribution of research studies on article citations and review methods from key scientific publishers, including IEEE, ScienceDirect, ACM, and Springer.

The study's selection principles and assessment flowchart are shown in Figure 2. We do not have an exclusion stage, but the literature we select must be from journals published in 2017-2022.

IV. ORGANIZATION OF THE IOT-BASED WEARABLE DEVICES

This section examines wearable IoT in the medical and healthcare sectors. Figure 3 shows a classification of device types and application areas for wearable IoT devices, including medical, sports, healthcare, and safety.

A. MEDICAL APPLICATIONS

Saadeh et al. [7] introduced a prototype IoT-based fall detection and prediction system for wearable devices tailored to the needs of individual patients. Fast mode for fall prediction (FMFP) and slow mode for fall detection was the most employed modes in this system (SMFD). The FMFP algorithm extracted seven traits that might occur before a fall, detected risk events that could lead to a fall, and advised patients to take preventative steps immediately. If a fall is identified as an event, the information will be sent to healthcare providers over the Internet right away. The suggested FMFP had a sensitivity and specificity of 97.8 percent and 99.1 percent, respectively, whereas the SMFD had a sensitivity and specificity of 98.6 percent and 99.3 percent.

Bisio et al. [14] introduced a wearable smart glasses prototype that can monitor Eye Blinks (EBs) using an Electrooculogram (EOG) signal transparently to the end-user. They presented a unique pre-filtering approach to minimize EOG noise and detect and count EBs. Their prototype is equipped with EOG sensors that can measure the EOG signal produced by the corneo-retinal standing potential from the front and rear of the human eye using simple electrodes mounted to the frame of the eyeglasses to perform an EB count. The findings revealed that their system could achieve very high EB detection accuracy and increase the likelihood of recognizing neurological illnesses in their initial stages. However, because of the significant differences in hardware design, EOG signal processing requires a distinct approach.

Malik et al. [17] proposed EyeCom, a retina-controlled device. EyeCom allows paralyzed persons to manipulate a computer mouse and choose or open apps using their eyes. The proposed gadget comprises infrared (IR) diodes, Xbee wireless sensors, Arduino microcontrollers, and accelerometers. EyeCom converts light into a digital signal using an infrared module. The motion signals are collected by the accelerometer and sent to the Arduino UNO microcontroller. Receiving all inputs from the wearable module and connecting to the computer through the USB connection is the responsibility of the Xbee radio and Arduino Leonardo microcontroller.

Zhou et al. [19] established a wearable IoT device based on an Improved Bayesian Convolutional Network (IBCN) for long-term, personal monitoring of individual activities. IBCN extracts features using convolutional layers, which improves the performance of wearable IoT devices by combining variable autoencoders and standard deep network classifiers. IBCN makes building lightweight, portable, and self-contained embedded body recognition systems easier and reduces the amount of insecure data collected by wearable IoT sensors. The researchers employed two datasets to test their system, and the results revealed that it might enhance accuracy, reliability, and low-power signatures.

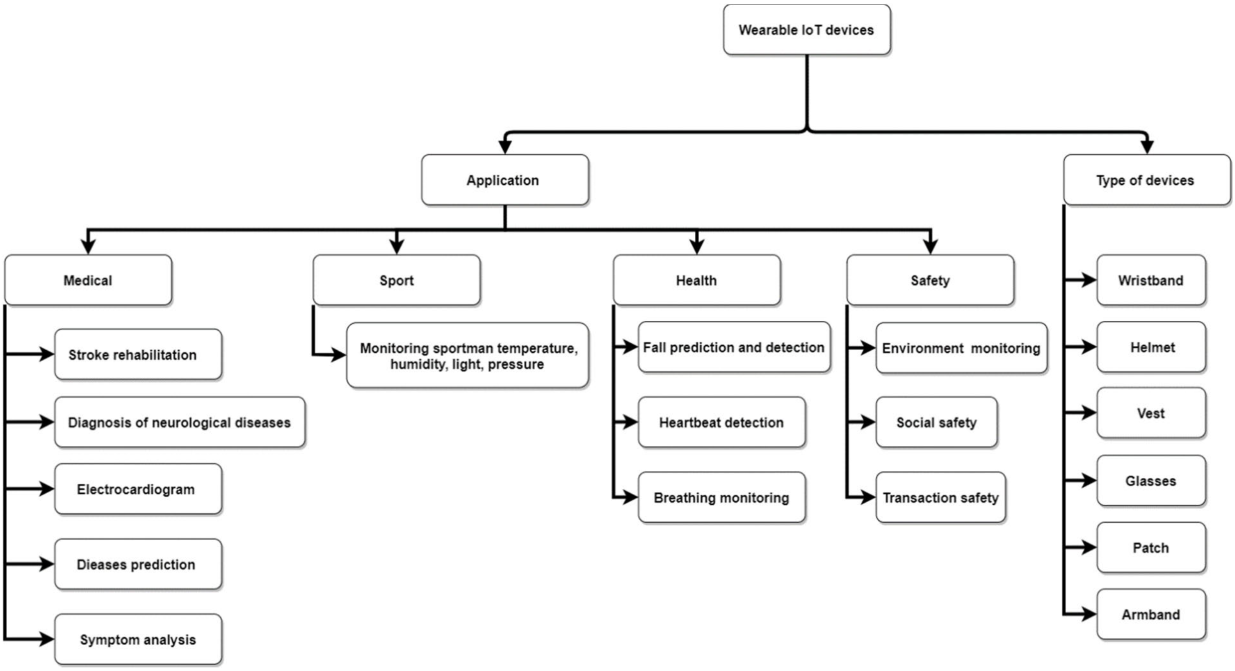

FIGURE 3. The taxonomy of wearable IoT devices.

In healthcare, Muthu et al. [21] suggested data mining analytics. They gathered patient information, trained on it, made predictions, and informed patients. They first built Generalize Approximate Reasoning basis Intelligence Control (GARIC) with regression rules to collect patient data from the IoT. The Boltzmann belief network, a deep learning method, is then utilized for training. Finally, they devised a Regularized Genome-wide association study (GWAS) to forecast illness. Compared to other approaches, the findings demonstrate that their suggested method achieves a precision rate of 96 percent and an accuracy rate of 96.33 percent.

Li et al. [27] designed an Android-based wearable health monitoring system with smartphone monitoring and alert operations for real-time monitoring of patient characteristics, including body temperature and pulse. The system includes a Bluetooth communication circuit, a body temperature acquisition circuit, and a pulse acquisition circuit. The observed data is forwarded to the Android system in real-time via a Bluetooth connection, and the data is displayed, recorded, and analyzed through its app. If the physiological data falls outside the normal range, an alarm signal will be forwarded to the guardian's mobile Internet device. The results show that the system can accurately capture the user's detection information and transmit it to the physician for remote analysis, providing further suggestions for the user. The alarm accuracy of the device can reach 97%, the temperature measurement error is less than 0.1°C, and the pulse measurement error is less than 2 BPM, which is very suitable for a wide range of applications.

Mohsen et al. [29] proposed a wearable sensor that monitors heartbeat, oxygen levels, and skin temperature powered by a solar collector. The harvester utilizing a low-power charging control system and a battery pack improves the node's ability to provide permanent energy and lengthens its lifetime. Data is transmitted wirelessly over the Wi-Fi network and stored in the Ubidots cloud server. The experimental result showed that the node works for 48 hours, and the average current consumed in 1 hour in wake-sleep mode is 6.13 mA.

For the life of the elderly, Liu et al. [53] proposed two applications using inertial measurement unit (IMU) sensors. They use the IMU for fall detection and physical activity level measurements. The dataset collected fall data using AiCare's wristband sensor, RockBand^{TM}(RB). The trained model was tested at a daycare center and achieved 98.04% accuracy, 94.7% precision, and 100% recall. After the experiment was done in this article, it was confirmed that it is more suitable for the elderly. Physical activity level measurements can track the effects of medications and doses. The proposed method builds a better infrastructure for the elderly.

Zhang et al. [54] proposed an integrated feature engineering structure to enhance the accuracy of clinical monitoring wearable devices. This framework used a singular spectrum analysis to extract high-level and data-resilient features daily. K-Nearest Neighbors (KNN) estimates the number of missing short heart rate portions. 61 patients who underwent pancreatic surgery were used to evaluate the proposed framework. The area under the receiver operating characteristic (AUROC) of a linear support vector machine (SVM) for predicting complications reached 0.8802.

Table 2 shows the ideas, algorithms/model, pros and cons, and datasets of studies on IoT-based wearables in medical

TABLE 2. Summary of recent research and other information in the field of medical applications on IoT-based wearables.

Reference	Main idea	Algorithm/Model	Advantage	Disadvantage	Simulation/Dataset/ Implementation
Saadeh et al. [7]	Wearable IoT-based fall prediction and detection device for patients	FMFP SMFD	Reducing the hardware complexity High power utilization burden	-	MobiFall dataset [8]
Bisio et al. [14]	Presenting a wearable smart glasses prototype that can monitor the EBs to increase the likelihood of recognizing neurological illnesses in their early stages	EB Detection Algorithm	High accuracy in EB detection High performance Reducing noise in the EOG signal Transparent technology	Great dissimilarity in hardware setup	EOG data is collected via wearable smart glasses.
Malik et al. [17]	EyeCom was proposed as a way for disabled individuals to interface with the machine.	Arduino microcontrollers Xbee wireless sensors IR diodes ADXL335 accelerometer	Building opportunities for paralyzed people to create their value	Operating only in two dimensions Time-consuming keyboard usage and calibration Wearing needs assistance	
Zhou et al. [19]	Based on IBCN, a wearable IoT device enabling innovative human activity identification.	IBCN	Portable, lightweight, and autonomous human identification systems Low power consumption High reliability	The source of the experimental data is unclear	Two datasets are utilized to identify a public incident.
Muthu1 et al. [21]	Analyzing patient information to predict disease	GARIC Boltzmann belief network Regulation GWAS	High accuracy Highly helpful	Lack of explainability	MATLAB
Li et al. [27]	Creating a novel Android-based wearable medical monitoring device	Android platform	Improving the detection efficiency High application value	No mention of the database source	
Mohsen et al. [29]	A wearable sensor powered by a solar collector	Pulse oximeter sensor Skin temperature sensor NodeMCU board Charging Controller Flexible PV Panels Battery	Self-powered Low power consumption	Not Convenient	Experimental performance of the device
Liu et al. [53]	IMU sensors for fall detection and physical activity level measurements	IMU sensors	Suitable for the elderly.	Imperfect	Using RB to collect data. Implemented in daycare centers
Zhang et al. [54]	an integrated feature engineering framework to improve the accuracy	Singular spectrum analysis	Significantly outperformed		Clinical study

applications. Besides, the evaluation criteria of the studies on IoT-based wearables in medical applications is shown in Table 3.

B. SPORT APPLICATIONS

Li [23] proposed a wearable sports fitness equipment system. The author used sensors to collect data, converted it into attitude angles with a low-pass filter, and analyzed gait information. This system's algorithm did not consider slope and road surface roughness. Experiment with people of different ages, weights, and genders. It is like the heart rate measurement with the Xiaomi Mi Band.

Huifeng et al. [26] introduced wearable sensors based on the Internet of Things (WS-IoT) for sports people to use as part of a continuous health monitoring system to gather health information and maintain workout records. Effective optimization machine learning approaches are presented to examine and monitor the health of athletes. Using an Ensemble Bayesian deep classifier (EBDC) technique, the system offers a wearable technology-based sportsperson health monitoring procedure. And data from mHealth datasets are utilized to examine the sensor-based health monitoring method. The dataset was collected using three sensor devices. The results demonstrate a 98.7% accuracy rate.

Jiang et al. [28] created an IoT-based wearable exercise rehabilitation monitoring device. A system is constructed to evaluate the efficacy of rehabilitation training that can monitor physical parameters in real-time, including exercise posture, electrocardiogram (ECG) signal, electromyogram (EMG) signal, and body temperature. Results indicate that

TABLE 3. The current wearable evaluation criteria used in medical applications on IoT-based wearables.

Reference	Accuracy	Sensitivity	Precision	True Positive	False Positive	Other Criteria
Saadeh et al. [7]	✓	✓		✓	✓	
Bisio et al. [14]	✓					
Malik et al. [17]						✓
Zhou et al. [17]	✓					
Muthu1 et al. [21]	✓	✓	✓	✓	✓	
Li et al. [27]	✓					
Mohsen et al. [29]						✓
Liu et al. [53]	✓	✓	✓			✓
Zhang et al. [54]		✓	✓			✓

TABLE 4. Summary of current research in the field of sports applications on IoT-based wearables.

Reference	Main idea	Algorithm/Model	Advantage	Disadvantage	Simulation/Dataset/ Implementation
Li et al. [23]	A wearable sports fitness equipment system	MPU6050	High accuracy	Not considering slope and road surface roughness	Collecting exercise data for people of different ages, weights, and genders
Huifeng et al. [26]	Introducing WS-IoT for sports people to monitor the health	– EBDC	– High accuracy	–	mHealth dataset
Jiang et al. [28]	Creating a wearable sensor and IoT -based sports rehabilitation monitoring device	– ECG sensor	– High stability	No mention of the database source	
Lan et al. [35]	Developing an IoT-based kinetic shoe using capacitors	– Capacitor-based sensor	– Reducing the power of the device	The hardware size is too bulky	Recruiting 10 volunteers
Fan et al. [37]	Proposing a human pose detection method for wearable devices	– Acceleration modulus algorithm – FFT	– Improving the accuracy of daily human posture detection	Experiments with only a small group of people	Emulate with an Android smartphone
Zhao et al. [40]	Proposing a system for real-time posture measurement	– MPU-6050 – Triaxial acceleration sensor – Three-axis gyroscope sensor	– Real-time – Effective – Low-cost	No interactive interface	Experiment on the human body

the system can closely monitor changes in the vital signs of the intended user and provide real-time feedback. These physiological data can aid physicians in formulating and modifying rehabilitation training programs.

Lan et al. [35] developed an IoT-based kinetic shoe using capacitors. It can detect daily activities through the charging rate of the energy harvester in the sole. The advantage of this method is that it can significantly reduce the device's power. The disadvantage is that the current hardware size is too bulky. A total of 10 volunteers were recruited for the experiment, and the results showed that the device could achieve 95% accuracy and reduce device power consumption by 57% compared to traditional sensors.

Fan et al. [37] used an Android smartphone to simulate a wearable device as a data acquisition device and proposed a human pose detection method for wearable devices. They used an acceleration modulo algorithm and performed a fast Fourier transform (FFT) to analyze the signal's frequency domain features to recognize the human body's motion posture, enhance the accuracy of day-to-day human posture detection, and reduce the error rate.

Zhao et al. [40] proposed a wearable system for measuring sports posture. This system uses sensors to measure the acceleration and angular velocity of the user's body rotation. The data are then monitored, processed, and displayed by the observing, computation, and display module. Ultimately, the network communication module realizes a TCP/IP-based real-time wireless data transfer monitoring framework and measuring device. The system applies to the instruction and practice of rehabilitation exercises. The results of experiments conducted on the human body indicate that the system can perform stable real-time monitoring, and the evaluation provided by the data analysis findings has a certain reference value.

Table 4 shows the ideas, algorithms/model, pros and cons, and datasets of studies on IoT-based wearables in sports

TABLE 5. The current wearable evaluation criteria used in sports applications on IoT-based wearables.

Reference	Accuracy	Sensitivity	Precision	True Positive	False Positive	Other Criteria
Li et al. [23]	✓					
Huifeng et al. [26]	✓		✓	✓	✓	
Jiang et al. [28]						✓
Lan et al. [35]	✓	✓				
Fan et al. [37]	✓				✓	
Zhao et al. [40]	✓					

applications. Besides, Table 5 shows the evaluation criteria of the studies on IoT-based wearables in sports applications.

C. HEALTHCARE APPLICATIONS

Yang et al. [9] presented an Internet of Things-enabled stroke rehabilitation system that relies on a smart wearable armband (SWA). Through three algorithms for machine learning: Support Vector Machine (SVM), Multi-Layer Perception (MLP), and Linear Discriminant Analysis (LDA), analyze and distinguish the characteristics of different hand movements and pass the classification complexity estimation algorithm (CCEA) and principal component analysis (PCA) to evaluate its performance. However, the accuracy will drop after removing the armband and taking it back again. Except for the nine gestures in the experiment, the other hand gesture recognition accuracy rates are low. They created a compact, comfy IoT smart wearable wristband with several little sensors to capture data. Off-line trained machine learning techniques based on MATLAB were used to differentiate features after signal pre-processing and feature extraction. According to the findings, all nine gestures were recognized with an average accuracy of 96.20 percent. Also, the practicality of CCEA and PCA is demonstrated by the high classification accuracy produced by the selected feature set, indicating that the system can effectively assist stroke patients in their rehabilitation process.

John et al. [10] introduced a multimodal data fusion strategy to increase beat detection accuracy in ambulatory monitoring. The electrocardiogram (ECG) and photoplethysmogram (PPG) signals were isolated in the wavelet domain using the discrete wavelet transform (DWT) and then merged using a weighted average to generate a fused feature signal. The peak detection method is applied to the final fused signal. More computing power and sensors are required to support this strategy. This study tested and analyzed the ECG and PPG signal inputs using the MIMIC III database. Noise is added to the PPG signal to corrupt it, but no motion artifacts are added. The suggested approach has a sensitivity of 99.69 percent and a positive predictive value of 99.64 percent, according to the data.

Jie Wan et al. [11] presented a wearable IoT-cloud-based patient monitoring system (WISE) that supported real-time individual medical monitoring through the body area sensor network (BASN) approach. They presented a system that collects data from the heartbeat, temperature, and blood pressure sensors, then sends it to the cloud through Wi-Fi and displays it on a wearable LCD. A mobile RFID reader connects to the Arduino, which contains all sensors for user identification. However, multiple sensors lead to the inconvenience of long-term wear, and battery life is an issue for this paper.

Fabrication, characterization, and validation of composite fabric ECG sensors were described by Hallfors et al. [12]. The self-powered wearable IoT sensor is made of nylon coated with reduced graphene oxide (rGOx). Signal reliability was measured using real-time ECG data. Graphene-coated composite fabrics for ECG have great potential as electrodes. However, the material's usefulness must be better appreciated.

Aliverti et al. [13] created a wearable respiratory and activity healthcare (WRAH) system to monitor day-to-day breathing patterns. They introduced a hybrid hierarchical classification (HHC) technique for distinguishing 15 complicated activities to improve accuracy and reduce calculation time. An HHC model can recognize seven dynamical exercises (such as jumping, walking, ascending and descending stairs, jogging, doing sit-ups/crunches, and squatting), seven static postures (such as forward, upright, and backward of the upper body, lying prone, lying to the left and right side and lying supine), and a series of transitions). In addition, the WRAH system can simultaneously monitor numerous users. The WRAH system, however, is limited in its ability to assess respiratory patterns. The experiment showed that the HHC model could achieve average accuracy and predictive time of 97.22% and 0.0094 seconds, respectively. It predicted activity quickly and robustly.

Wu et al. [15] showed a small wearable sensor patch that could measure body temperature, PPG, and ECG, among other physiological signals. All sensor data will be transferred to a gateway that can be fixed (computers) or portable (smartphones, for storage and subsequent analysis of health data via a Bluetooth low-energy (BLE) module. Furthermore, during transmission, AES-128 encryption is used to preserve the confidentiality and privacy of subjects. The findings of the experiments show that real-time blood pressure monitoring using wearable sensor patches and estimation algorithms is reliable when properly calibrated. It can be utilized daily for remote long-term continuous blood pressure monitoring.

Manas et al. [16] demonstrated a wearable physiological monitoring method to detect a human subject's fall and connect to an Android platform over a wireless network. The device uses three sensors: an impact sensor, a heart rate sensor, and a temperature sensor to collect data, send it to the Android platform through Bluetooth, and establish a network database via the mobile phone network. The monitoring device analyzes the data and immediately notifies medical staff if there is a danger. Compared to other devices, the device proposed in this paper lacks other functional sensors to create a more comprehensive data analysis. This paper compared the pulse measurement with the commercially available Xiaomi MI band 2. The result showed a maximum error of +2.54%.

Ali et al. [20] introduced health detection sensors that measure heart rate, SpO2, and body temperature. The sensor employs light-emitting diodes (LED) to determine pulse oximetry and heart rate and alternately turns on the RED and infrared LEDs to avoid variable finger widths or skin tones impacting the findings. The data is transferred to the Android phone via the HC-05 Bluetooth module and then to the Thingspeak Internet server using the ESP8266 WIFI module. Between their suggested detecting sensor and the ChoiceMMed pulse oximeter, there was a maximum difference of 2%.

Cardiovascular disease is the main cause of death for many older people. Beach et al. [38] developed an ultra-low-power wrist-worn ECG monitor based on the IoT, which is lightweight and convenient for users to wear for a long time. In addition to measuring raw ECG waveforms and heart rate, the device can also capture location and activity. Through SPHERE, a Sensor Platform for HEalthcare in a Residential Environment, data is collected to assist people in confirming their health status. According to the experimental results, the developed device can reduce power consumption while maintaining performance and allowing the battery life to exceed a month.

Li et al. [39] proposed an IoT platform concept for wearable devices and cloud computing to process data about pregnant women. The platform has a perception, network, and application layer. The perception layer collects physiological data and transmits data through the network layer. The application layer covers all services related to pregnant women. The platform enables pregnant women to have perfect care without frequent trips to the hospital. Through the questionnaire, it is known that pregnant women have a high degree of acceptance of this platform, and the concept of the platform can be operated. Finally, the challenges of IoT platforms are listed, and the basic questions for building IoT platforms are provided.

The early diagnosis and management of medical disorders can be aided by wearable devices (WDs). However, the usage of the WDs that are now on the market by senior people is less well understood. Kekade et al. [50] assess the wearable technology's utility and actual usage among seniors. They used a survey questionnaire as the foundation for their technique. The findings indicate that more than 60% of seniors were interested in wearable technology in the future and favored its usage to enhance physical and mental activity. As a result of their research, it is recommended that clinical testing be conducted equally on males and females to improve the advantages and dependability of the tested technology for both sexes.

Recent developments in biosensor systems for wearable health devices, such as heart rate (HR) sensors, have made it possible to assess and comprehend the physical needs of construction workers continually. In a case study of 19 employees on construction sites, Hwang et al. [51] looked at the efficacy of an affordable HRR-based physical demand measuring system employing wristbands. By examining data on parameters impacting physical demands, the study seeks to determine if this continuous assessment can catch any major fluctuations in physical demand (e.g., work tasks, individual and environmental factors). The findings demonstrate that workers' physical demands vary greatly depending on their working schedules, the cumulative effects of their jobs, and personal and environmental parameters (e.g., age and heat stress). This study showed that using a bracelet to record employees' substantial high physical demands while continually working is practical and effective.

Even with the most advanced equipment, treating and monitoring COVID-19 possible infected patients remains a difficult task. To measure several vital indicators connected to COVID-19, Al Bassam et al. [52] presented a wearable monitoring system based on the IoT. By tracking patients' real-time GPS data, the system automatically notifies the relevant medical authorities about any quarantine breaches for potentially infectious patients. The wearable sensor is connected to an edge node in the IoT cloud when data is collected and analyzed to identify the body's health status. The proposed system is constructed with three-tiered functionalities: an Android web layer for mobile devices, a cloud layer using an Application Peripheral Interface (API), and a layer of wearable Internet of Things sensors. Each layer has its functionality. The data is first measured from the IoT sensor layer to identify the health symptoms. For preventative measures, notifications, and quick responses, the information is stored in the cloud database using the following layer. Notifications and alarms are sent to the possibly affected patient families by the Android mobile application layer. In addition, they describe how a wearable remote system may be used as a monitoring device to track a COVID-19 patient's health and recovery.

Yan et al. [55] proposed EMOGLASS. They used CNN to recognize facial expressions. The proposed glasses can detect seven facial expressions. The glasses can be paired with an app to allow users to self-monitor and improve their mood. Three datasets were constructed with 15 participants and tested on facial recognition. The results show that the accuracy of detecting facial expressions in wild conditions is 73%, which means that the proposed EMOGLASS can achieve high robustness.

Table 6 shows the ideas, algorithms/model, pros and cons, and datasets of studies on IoT-based wearables in healthcare applications. In addition, the evaluation criteria for IoT-based wearables in healthcare applications are shown in Table 7.

TABLE 6. Summary of recent research and other information in the field of healthcare applications on IoT-based wearables.

Reference	Main idea	Algorithm/Model	Advantage	Disadvantage	Simulation/Dataset/ Implementation
Yang et al. [9]	IoT-enabled stroke rehabilitation system, which was based on SWA	– LDA、MLP, and SVM – CCEA – PCA	– Unobtrusive, comfortable, and simple to operate. – Improving robustness – Increasing the accuracy of gesture recognition	– The accuracy dropped after the armband re-taken – Except for the nine gestures in the experiment, the recognition accuracy of other gestures is lower	Experiment on two males and one female who are non-disabled.
John et al. [10]	IoT sensors are used in a multimodal data fusion approach.	– DWT	– Improving detection accuracy in ambulatory conditions – The best detecting performance with the least amount of battery usage	– Need more computational power and sensors – Lack of synthetic motion artifacts	MIMIC III database
Jie Wan et al. [11]	A health monitoring system based on wearable IoT-cloud	– BASN framework	– Online health monitoring – Retrieving the most valuable information precisely – Data visualization – Disease identification and notification	– The inconvenience of multiple sensors – Battery life problem.	Experiment with various functions of sensors on the human body.
Hallfors et al. [12]	Composite fabric ECG sensors are discussed in terms of manufacture, characterization, and validation.	– ECG sensors comprised of nylon with rGOx coating	– Graphene-coated composite fabrics for ECG have great potential as electrodes	– Sensor impedance is dynamically adjusted to match skin impedance – ECG without motion artifacts – Not integrated into the system-on-chip (SoC) ECG system	A volunteer's ECG was recorded in real-time.
Aliverti et al. [13]	Developing a WRAM system to comprehend daily breathing patterns	HHC algorithm	Improving the recognition rate Saving computational time Recognizing 15 activities	The WRAH system's ability to evaluate the breathing pattern is restricted.	Twelve individuals were directed to complete 15 tasks in a specific order in order to obtain the data.
Wu et al. [15]	A wearable sensor patch to measure and encrypt transmission security and privacy	BLE module AES-128 encryption Microcontroller: ARM Cortex M0 ECG Sensor: AD8232 Temperature sensor: Si7051 Customized PPG sensor	Convenience and long battery life Long and short-distance data transmission Visualize monitoring data High data security	Lack of proactive notification	Testing on chests of three people using sensor patches.
Manas et al. [16]	A wearable physiological parameter monitoring device to identify a human subject's fall and proactively notify medical staff in case of danger	Temperature sensor: LM35 Heart rate sensor: Analog filter design and Digital filter design Impact sensor: ADXL335 Online database: Google's cloud	Detect a human subject's fall. Immediately notify medical staff if there is a danger	Lack of other functional sensors to create a more comprehensive data analysis	Comparing the pulse measurement with Xiaomi MI band 2.
Ali et al. [20]	Health monitoring sensor system for simultaneous measurement of heartbeat rate, SpO2, and body temperature	– Bluetooth module: HC-05 – Wi-Fi module: ESP8266 – Arduino A digital DS18b20 thermometer	– Data transfer convenience – High suitability Data visualization	Data transmission security	Experiment on five people

TABLE 6. ***(Continued.)*** **Summary of recent research and other information in the field of healthcare applications on IoT-based wearables.**

Beachet al. [38]	Developing an ultra-low-power wrist-worn ECG monitor based on the IoT	– SPHERE platform	– Low power consumption – High battery life – Lightweight		Collecting data on the SPHERE platform
Li et al. [39]	IoT platform for pregnant women		– Convenient – Multifunction	Not Implemented	
Kekade et al. [50]	The importance and practicality of wearable technology for seniors	– Survey questionnaire	– Demonstrating the existing usage and availability of wearable devices for enhanced living circumstances	The majority of respondents to the survey were women.	Completed by 233 people in four different age groups (45, 46, 65, and 75 years old)
Hwang et al. [51]	Wristband-type wearable devices for construction workers' health	– Photoplethysmography sensor	– Giving insight into effective management strategies for managing excessive physical demands – More accurate measurement of physical needs		Collecting from 19 construction workers, 14 on-site and 5 off-site workers
Al Bassam et al.[52]	A wearable IoT-based gadget to track the symptoms of COVID-19 distant patients in quarantine	– Feature extraction – CNN	– It can be used in automated healthcare systems – Reducing the stress on doctors	Only simulation experiments	
Yan et al. [55]	Enhancing Self-Awareness of Emotional Health	– CNN	– High robustness – High integrity	Not detecting complex emotions	Collected data by 15 participants.

TABLE 7. **the current wearable evaluation criteria used in healthcare applications on IoT-based wearables.**

Reference	Accuracy	Sensitivity	Precision	True Positive	False Positive	Positive Predictive Value	Other Criteria
Yang et al. [9]	✓						
John et al. [10]	✓	✓	✓	✓	✓	✓	
Hallfors et al. [12]							✓
Aliverti et al. [13]	✓						✓
Wu et al. [15]							✓
Manas et al. [16]							✓
Ali et al. [20]							✓
Beachet al. [38]	✓						
Kekade et al.[50]							✓
Hwang et al. [51]							✓
Al Bassam et al.[52]	✓			✓	✓		✓
Yan et al. [55]	✓						✓

D. SAFETY APPLICATIONS

Li et al. [18] created wearable transdermal alcohol (TAC) sensors in the style of an armband or bracelet for monitoring vapor-phase alcohol concentrations in perspiration. They picked a two-lead electrochemical fuel cell alcohol sensor as the principal sensor. It converts ethanol to an electrical signal and monitors alcohol vapor concentration in parts per million (ppm). With a one-minute temporal resolution, the sensor can identify vapor-phase alcohol in sweat from 0.09 ppm to over 500 ppm and discriminate between different dosages of TAC data. Furthermore, the sensor can obtain TAC curves at low dosages under well-controlled settings (1-2 standard drinks). However, ambient gas, temperature, and intense perspiration may affect the TAC sensor's accuracy.

Xu et al. [22] proposed a human behavior recognition method for wearable devices and compared which of the three classifier models is the most suitable data mining technique for analyzing information. The artificial neural network (ANN) is used to design the human behavior recognition model. The results showed that the compound Bayes classifier has the highest accuracy, and the three indicators of precision, sensitivity, and specificity all perform well. The accuracy of human action recognition can reach more than 75% when the number of neuron nodes is 11. This article provided a reference for other research applications.

Wang et al. [24] concentrated on protecting patients' information during medical data exchange. Based on the Wireless Body Area Network, a lightweight and fine-grained data exchange strategy is devised. Attribute Partially Hidden Access Control is the upgraded version (APHAC). Users can only access data if their characteristics align with the data owner's access policy. The storage and processing overheads are considered in the simulation experiment. When the number of characteristics approaches 100, the APHAC method saves roughly 500 milliseconds compared to the regular Ciphertext Policy Attribute Based Encryption technique. It may be stated that the encrypted access control technique described in their study prevents end users from spending too much time in front of their computers.

Jafarzadeh et al. [25] described an inexpensive wearable sensor vest and an open-source software framework for social robotic systems that utilize the IoT. Gestures, vision, temperature, touch, distance, and a wireless communication module are all included in the vest. The stated architecture is compatible with any social robot equipped with a general-purpose graphics processing unit (GPGPU), a robotics operating system, and an Internet connection. This architecture's modular nature makes it simple for developers to add, delete, and update complicated behaviors. They utilized the HTTP protocol for communicating with the social robot via the Internet in a two-way manner. In the computer languages Python, C, and C++, developers may change or add nodes. Their architecture may be utilized to create more complex social humanoid robot behaviors.

Gladson et al. [30] presented an ultra-low voltage low-noise amplifier (LNA) to meet the requirements of battery-powered communication systems. LAN has a low-power mode and a high-power mode. This study has been adapted from the analysis of gain, noise figure, and Linearity. Simulations were done using the Cadence SpectreRF circuit simulator, and the results showed that reducing the voltage provided 18.78dB of gain.

Personal privacy leakage has always been an essential topic in the field of IoT. Can et al. [34] used IoT-based wearable wristbands to collect heart activity data to monitor users' stress levels during different events. In addition, they transmit the collected data to a centralized server through a federated deep learning algorithm instead of the entire server. This method can reduce the burden on the communication network and avoid personal data leakage.

Pairing a wearable device with a mobile device will transmit a large amount of data. The content of these data and whether users will agree or not are critical issues in the IoT. Lee et al. [36] extracted stored data from wearable devices running on Tizen, watchOS, and Android Wear platforms. The experimental results show that a large amount of sensitive data is transmitted without notification to the user, which will cause a large amount of damage—privacy and security risks. Future work should concentrate on enhancing the method of data transmission or actively notifying users of the type of data that will be transmitted to increase users' awareness of personal data security.

Table 8 shows the ideas, algorithms/model, pros and cons, and datasets of studies on IoT-based wearables in safety applications. Besides, Table 9 shows the evaluation criteria of the studies on IoT-based wearables in safety applications.

V. DISCUSSION

We reviewed and analyzed the studies on IoT wearable devices. This section addresses the research questions from Section 3.

☐ **RQ1: What is the number of publications over time?**

Figure 4 shows the number of publications in the past five years. Statistics show that research on IoT wearables has increased over time. The lower number of publications in 2022 than in 2021 is because the literature search was in early 2022; as science and technology advance, more and more research is conducted on IoT wearable devices. The result shows that IoT wearable devices will soon receive more attention in the research field.

☐ **RQ2: What are the evaluation factors used in wearable IoT?**

The studies on IoT wearable devices require evaluation factors to justify the study's findings. These evaluation factors are divided into the model evaluation and device performance. Figure 5 shows the distribution of evaluation factors used in the studies. We can see that 71% is model evaluation and 29% is device performance. The proportion of model evaluation is more than device performance. Research on wearable devices is more focused on the quality of the proposed model. However, both evaluation factors are essential for IoT wearables. The criteria used to evaluate the models were accuracy, prediction, sensitivity, true positive, false positive, and positive predictive value. Fig. 6 shows the distribution of evaluation factors of model evaluation. The highest proportion of the model evaluation factor is accuracy. We can see that accuracy of the model proposed in the study is essential. However, studies must select appropriate evaluation factors to support the findings in addition to using the accuracy of the most common evaluation factors.

☐ **RQ3: What are applied communication technologies in wearable IoT?**

The research studies on detecting the state of the body will require sensors to collect body information. The most basic data collected in these studies are heart rate and body temperature. IoT wearables often contain sensors that monitor heart rate and body temperature. Other sensors used to monitor the health of the body return data such as blood pressure, impact, and pulse oximetry. IoT wearable devices have various sensors to send back data after monitoring the body. Suppose you can monitor every kind of data of your body. In that case, you will be able to know more about your physical condition and then make reminders, improvements, notifications, and so on.

TABLE 8. Summary of recent research and other information in the field of safety applications on IoT-based wearables.

Reference	Main idea	Algorithm/Model	Advantage	Disadvantage	Simulation/Dataset/ Implementation
Li et al. [18]	TAC sensor that may be worn as a bracelet or armband.	Two-lead electrochemical fuel cell alcohol sensor will serve as the primary transducer.	TAC curves may be obtained using the sensor even at low dosages	– Interfering gases and temperature can affect TAC sensor readings Sweat rate may affect the TAC sensor	Recruiting three male subjects
Xu et al. [22]	Comparing classifiers and recognition models	– ANN Compound Bayes classifier	Clear results	– Little data set Low completeness	Implementation dataset
Wang et al. [24]	Designing data exchange strategy for wearable telerehabilitation	APHAC	– Avoiding leaking user privacy Reducing storage overhead	High complex calculations	The simulation experiment factors include the computational overhead and storage overhead
Jafarzadeh et al.[25]	Presenting a low-cost wearable sensor vest and an open-source software architecture for social humanoid robots	– GPGPU CNN	– Easy to develop It can be used in many medical applications	Public Internet may cause latency	-
Gladson et al. [30]	LNA operating at ultra-low voltage	– LNA	– Ultra-low voltage – Low power operation		Cadence SpectreRF circuit simulator
Can et al. [34]	Developing an IoT-based wearable wristband to collect heart activity data	– Federated deep learning algorithm	– Avoiding data leakage – Reduce the burden of communication network	- Teachers from public schools in Turkey collected in the workshop - Innovative Training Network event in Istanbul Data from the Trier Social Stress Test implemented in the lab.	

TABLE 9. The current wearable evaluation criteria used in safety applications on IoT-based wearables.

Reference	Accuracy	Sensitivity	Precision	True Positive	False Positive	Other Criteria
Li et al. [18]						✓
Xu et al. [22]	✓	✓	✓			
Wang et al. [24]						✓
Jafarzadeh et al.[25]	✓	✓				✓
Gladson et al. [30]						✓
Can et al. [34]	✓					

The most used technique for transferring data is Bluetooth. Bluetooth can perform short-distance transmission without needing a network, so it is widely used in IoT wearable devices. Because now everyone has a mobile phone, the wearable device transmits data to the mobile phone through Bluetooth and then transmits it to the cloud through the mobile phone network.

☐ **RQ4: What are the challenges and open issues in wearable IoT?**

We will discuss the following IoT wearables issues and challenges regarding security, integrity, interpretability, and device power, device power, economics, and comfortability for patients

Security: Attacks are encountered during data transmission, and the transmitted data is tampered with or omitted. This situation can lead to the inability to make correct judgments or even mislead the user and expose the user to danger. It is important to encrypt the transmitted data to prevent an attack from affecting users. Very few articles take action on data security, but it is an issue that must be taken seriously.

Integrity: There are many kinds of sensors in IoT wearable devices and a lot of data the body needs to monitor. It is perfect to have all the sensors that can be monitored on a device. However, arranging all the sensors on the device makes the wearable device heavy and inconvenient. Integrating all the sensors and improving the ease of wearing will be challenging.

Interpretability: Models using machine learning algorithms or deep learning algorithms have black-box problems, and it is impossible to know how the model decides. What

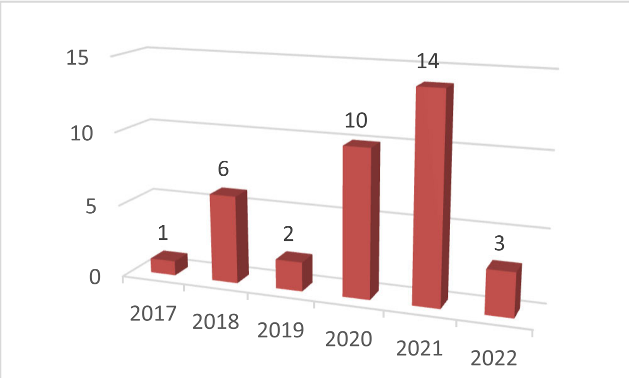

FIGURE 4. Number of publications over times.

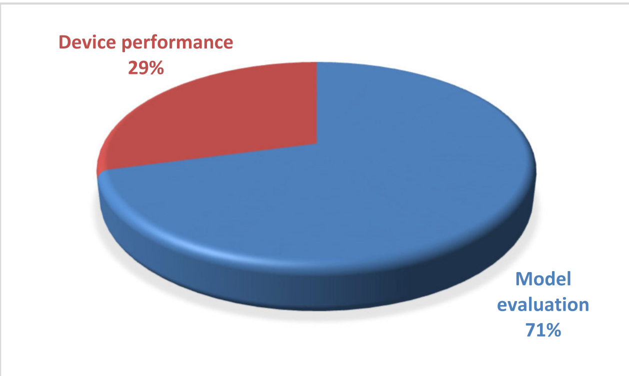

FIGURE 5. Distribution of elevation factors.

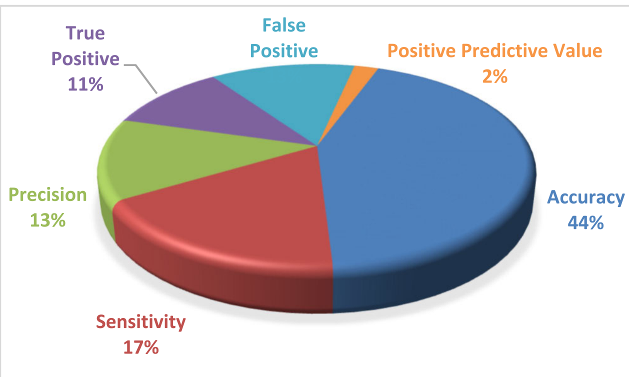

FIGURE 6. Distribution of model evaluation.

reasons or conditions the model is based on to make relevant decisions must be understood before people can trust the model's decision. Models with interpretability can clearly understand the model's shortcomings and improve them. However, it is also a challenge for the model to be interpretable.

Device power: Wearable devices need electricity to make sensors work. The best wearable devices use the least power to operate, so users do not have to charge the wearable device constantly. A fully functional wearable will require more sensors, which will require more power. Wearable devices add additional batteries to load the required power, reducing the convenience of wearable devices. Wearables must consider both power and functionality for users' convenience.

Economics: Wearable devices consist of sensors and other components from an economic perspective. When wearables become readily available and expected by all, economic growth will result. The popularity of wearable devices coincides with a rise in demand for related components. The demand for raw materials increases the country's economic activity. Economic growth will result when wearable devices are utilized in everyday life and satisfy most people's needs.

Comfortability for patients: Numerous wearable devices are utilized in medicine to monitor a patient's condition. The patient's fatigue in the face of the disease results from the discomfort caused by the disease. It is necessary to pay close attention to their comfort to care for the patient's mind. In addition to monitoring the patient's body values, a wearable device must also be comfortable. To increase patient compliance, wearable devices that come into contact with the user's skin should utilize low-sensitivity materials and be lightweight.

Wearable devices used in medical, health, and sports fields are based on detecting body values to observe physical conditions. The future research direction can establish the basic detection body values on the platform and use the relevant values on the platform to apply to different fields of operation processing. If different domain knowledge is aggregated on the platform, it will help to understand the impact of changes in human body values and to understand the human body better. People can monitor body changes in real time on the platform and pay more attention to body warnings. Real-time monitoring combined with knowledge in the medical field makes it convenient for people to maintain their health without having to spend time frequently going to the hospital for examinations.

VI. CONCLUSION

We selected 30 research papers for analysis by screening criteria in this paper. According to RQ1, research on wearable devices is increasing yearly, and wearable devices have attracted much attention. According to RQ2, the evaluation factors of IoT wearable devices can be divided into factors for model evaluation and sub-components for device evaluation. The factor ratio of the evaluation model was 39% lower than the device evaluation factor, which accounted for 61%. We observed a high proportion due to the diversity of factors used to evaluate the device. It can be seen that the most commonly used factor to evaluate the model is accuracy at 48%. RQ3 describes communication technologies used in IoT wearables. Finally, we discuss the open issues and challenges of wearable devices. This paper only discusses 30 research papers and provides a reference for evaluation factors and field selection for research in wearable IoT.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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