Intelligent Wearable Systems: Opportunities and Challenges in Health and Sports

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Wearable devices or wearables, designed to be attached to the human body, can gather personalized real-time data and continuously monitor an individual's health status and physiological disposition in a non-invasive manner. Intelligent wearables integrate advanced machine learning (ML) algorithms to process complex data patterns and provide accurate insights. As a result, intelligent wearables have emerged as a groundbreaking innovation in the fields of sports and health, introducing a new paradigm in kinematic analysis and patient data evaluation. For example, virtual coaches offer feedback on athletes' performance, while virtual physicians assist in customizing medication for patients. This article provides an overview of various types of intelligent wearables and their applications in health and sports, categorizes ML algorithms, and introduces the wireless body area sensor network (WBASN) used for communication in wearable sensors. Additionally, we discuss potential challenges and development directions that could shape the future of intelligent wearables and propose effective solutions for their continued enhancement. This article offers valuable insights into the exciting potential of intelligent wearables to transform healthcare and sports.

CCS Concepts: • **Computer systems organization → Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

Additional Key Words and Phrases: Artificial intelligence, Machine learning, Wearables, Health, Sports

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1 INTRODUCTION

We are experiencing rapid growth on the Internet of Everything (IoE) era, connecting not only devices and sensors but also people, processes, and data. Wearable devices play an integral role in the IoE ecosystem by enabling new forms of communication between people and machines [1]. Wearable devices are small, body-worn devices equipped with sensors. These sensors can detect and analyze physiological vitals and signals such as heart rate and motion. As people seek greater productivity, quality of life, and comfort, commercial non-invasive wearable devices are becoming widely available. For example, smartwatches monitor sleep and exercise, while smart glasses display notifications and weather forecasts. Fitness trackers count steps and calories burned, and smart clothing incorporates sensors that track health metrics. Most wearable devices are non-invasive, using sensors that are safer, more accessible, and more convenient. For clarity, this article assumes wearables are non-invasive.

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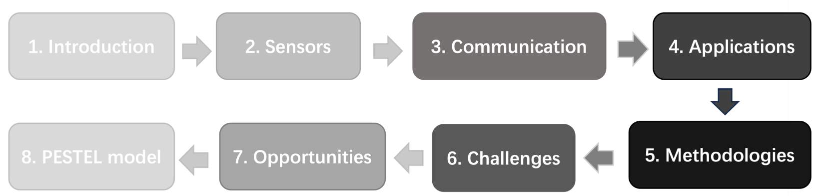

Fig. 1. The survey structure

The advent of numerous wearables has enabled us to gather a greater volume of high-quality multi-modal data. However, traditional data analysis methods are subject to limited adaptability, limited feature extraction, and limited efficiency. Limited data adaptability means the results tend to become less precise if the data or environment changes [2]. Limited feature extraction means that traditional methods are unable to effectively identify meaningful patterns in high-dimensional data when feature extraction is restricted [3]. Limited efficiency means when dealing with large amounts of data. Traditional methods tend to be time-consuming and expensive [4]. Given these constraints, there is a significant demand for generalized, accurate, and timely data analysis. With the continuous development of artificial intelligence (AI) technology in recent years, especially the method of data analysis based on machine learning (ML), it has the potential to break through the limitations of traditional methods and provide a valuable direction for data analysis of wearables. In the healthcare industry, ML can aid doctors in accurately detecting diseases and devising personalized treatment plans for patients by analyzing vital signals obtained from sensors. For instance, by analyzing data from wearable heart rate monitors and oxygen level sensors, ML models can detect early signs of heart disease or any other cardiac issues. In a similar vein, within the realm of sports science, ML techniques can analyze data gathered from physiological sensors used by athletes. This enables informed evaluations of athletes' performance, proactive injury prevention, and the enhancement of athletic capabilities. For example, analyzing data from motion sensors and muscle activity trackers can help determine athletes' form and technique during workouts or competitions. Coaches can then provide customized guidance to improve performance and reduce injury risks. As a result, AI and ML have significant promise for enabling new insights from wearable data. By overcoming the limitations of traditional methods, ML unlocks the potential of wearable data to enable wider benefits, advancing AI for personalized monitoring and diagnosis.

Numerous literature reviews exist within the realm of wearable device sensors. These reviews offer extensive and thorough introductions to sensor technology, communication technology, and their applications across various domains, providing invaluable insights for researchers in the field.

For instance, Seneviratne et al. undertook an extensive survey and classification of over 100 commercial wearables, delving into aspects such as communication technology, power consumption, battery technology, safety, and manufacturing [5]. In a similar vein, Ometov et al. conducted a survey on commercial equipment related to wearables and explored their applications in medical, sports, and entertainment sectors [6]. Niknejad et al. executed a thorough survey on the application of wearable devices from 2010 to 2019, providing an analysis of the current state of affairs and highlighting challenges within the sector [7]. Majumder et al. offered an in-depth exploration of the relevant sensor systems from six aspects of the medical system, further detailing the methods of communication and transmission within medical system applications [8]. Dian et al. categorized the applications of wearable devices into four sections: health, sports, tracking, and security. They concluded their study by posing corresponding challenges for sensor technology [9].

Table 1. Comparative analysis of surveys

Study	Sensor& Device	Network	Applications	ML	Challenges	Opportunities	PESTEL Analysis
Our Survey	18 sensors, 19 devices	Communication, IoB, WBASN	Health: 25, Sports: 10	categories, principles, scenarios, models (26)	17	15	5 external factors
Seng et al. 2023 [10]	4 devices	Communication	Health:10, Sports: 5	scenarios, models (10)	6	3	-
Kumar et al. 2023 [11]	5 devices	Communication	Health: 7	categories, scenarios, models (4)	2	4	-
Subhan et al. 2023 [12]	18 devices	-	Health: 11	scenarios	17	-	-
Veeman et al. 2022 [13]	4 sensors, 8 devices	Communication	Health: 12	scenarios	-	5	-
Nahavandi et al. 2022 [14]	6 devices	-	Health: 11	categories, principles, scenarios, models (11)	7	4	-
Sabry et al. 2022 [15]	10 sensors	-	Health: 12	categories, models (16)	8	3	-
Chidambaram et al. 2022 [16]	3 devices	-	Sports: 5	scenarios, models (11)	6	3	-
Junaid et al. 2022 [17]	15 sensors	-	Healths: 5	categories, models (12)	6	-	-
Site et al. 2021 [18]	10 sensors	-	Health: 6	categories, principles, scenarios, models (17)	-	5	-
Perez et al. 2021 [19]	8 sensors	Communication	Health:3, Sports: 3	scenarios, models (6)	-	-	-
Phatak et al. 2021 [20]	9 sensors	AIBSNF	Health: 4, Sports: 5	scenarios, models (12)	4	3	-
Chawla et al. 2020 [21]	12 devices	Communication	Health: 10	categories, scenarios	-	-	-
Nithya et al. 2021 [22]	5 sensors	-	Sports: 5	scenarios	3	1	-
Rana et al. 2020 [23]	1 sensor, 8 devices	-	Sports: 3	scenarios, models (12)	6	5	-

The numbers in the table reflect the quantity of respective criteria for each survey.

While these studies indeed furnish researchers with a detailed and comprehensive understanding of the intelligent wearables domain, they tend to overlook the application of ML in sensors. Recently, the integration of ML and wearables in the healthcare and sports sectors has garnered significant attention, leading to many review articles aimed at offering readers a more profound understanding of ML applications within the wearable technology domain. We used three keywords: "Machine learning/Artificial intelligence", "Health/sports", and "Wearables" to retrieve related reviews. We evaluate each article in multiple dimensions. These comparisons are recorded in Table 1, which presents a detailed comparative analysis of surveys pertinent to intelligent wearables.

Unlike these surveys, our study amalgamates all categories from the reviewed literature while providing an up-to-date review. Our survey provides a comprehensive overview of intelligent wearables across seven key areas: sensors, communication, applications, algorithms, challenges, opportunities, and the political, economic, social, technological, environmental, and legal (PESTEL) framework. The objective of this survey is to synthesize existing literature on intelligent wearables in health and sports, provide an up-to-date review of the field, and offer readers valuable insights into this interdisciplinary area. The key contributions of our survey include:

- Our article provides a uniquely comprehensive overview of intelligent wearable systems and their application in health and sports fields. We conduct an up-to-date literature review investigating all smart wearable system aspects with a detailed classification and discussion of each aspect.
- We provide the most extensive collection of ML models and methods currently applied in wearables, with a focus on algorithmic advances. This highlights the diverse possibilities of ML to improve health and sport fields and expand relative applications.
- We offer novel interdisciplinary perspective on opportunities and challenges when implementing intelligent wearables. This provides valuable insights for researchers, developers and stakeholders in health and sports fields.
- We employ the PESTEL framework analysis to examine external non-technological factors (political, economic, social, technological, environmental, and legal), which can influence the development and adoption of intelligent wearables in health and sport fields.

The structure of the article is summarized in Figure 1. Section 2 categorizes and describes various wearable sensors and their principles. Section 3 explains network communications and related technologies in depth. Section 4 introduces applications of intelligent wearables in medicine and kinematics. Section 5 introduces ML algorithms for wearable data from an algorithmic perspective. Sections 6 and 7 discuss opportunities and challenges related to intelligent wearables, respectively. Finally, Section 8 uses the PESTEL framework to analyze external factors that may impact the intelligent wearables industry.

2 WEARABLE SENSORS

Throughout this section, our aim is to provide an overview of the various types of sensors commonly employed in the medical and sports domains. The sensors discussed in this section can be broadly categorized into five main groups: motion sensors, bioelectric sensors, biometric sensors, environmental sensors, and optical and chemical sensors. Additionally, we will delve into the definition of flexible sensors and wearable devices. It is crucial to emphasize that our primary focus lies on classifying and describing sensor types, rather than examining commercial wearable devices.

Before introducing each sensor in detail, we have indicated the potential locations on the human body where various types of sensors may be utilized in different research studies in Figure 4. Additionally, a more elaborate depiction of the placement of diverse sensors across the human body can be found in Table 2.

2.1 Motion sensors

Motion sensors, also known as inertial sensors, are capable of converting inertial forces into electrical signals that can be used to measure object motion, such as acceleration, inclination, and vibration. The accelerometer (ACC) and gyroscope (GYRO) are the primary inertial sensors responsible for measuring inertial acceleration and angular rate separately. In addition, most daily human activities

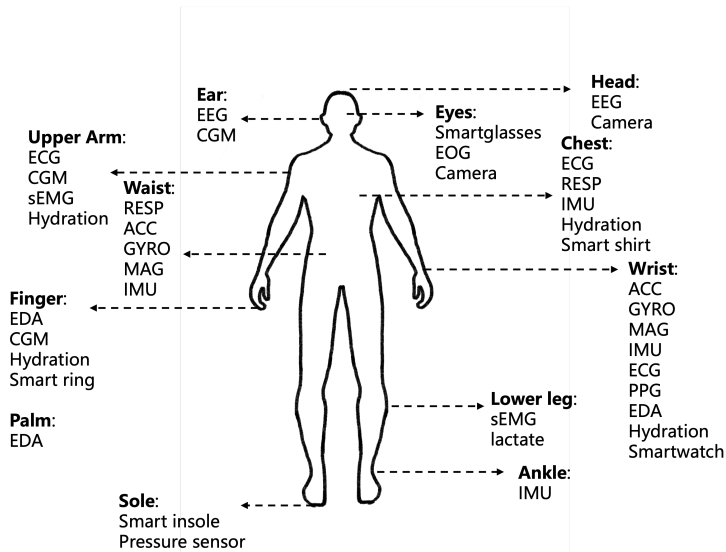

Fig. 2. Diagram of the placement of different wearable sensors on the human body

need to measure acceleration, angular velocity, or more dimensional information. Therefore, the more popular one is an inertial measurement unit (IMU), multiple ACCs, and GYRO assembly. Some IMUs have additional magnetometers (MAG) to measure the magnetic field surrounding the system. In this case, the system is a magneto-inertial measurement unit (MIMU).

A single ACC or GYRO could help us monitor and detect motion. Regarding the use of a single ACC, it has been demonstrated that it has the capability to gauge the intensity and motion classification of activities, including fall detection, gait monitoring, and measurement of physical activity. In light of their compact size, ACCs are often integrated into various devices, such as smartphones and smartwatches. In situations where the measurement or maintenance of orientation and angular rate is the primary concern, gyroscopes are typically employed. For example, gyroscopes could be implemented to detect ankle sprains, and monitor falls.

Compared with a single inertia sensor, IMU or MIMU is more popular because it integrates the characteristics of ACC, GYRO, and MAG to obtain multi-dimensional information. They are used in various applications of human activities, such as disease classification, gait detection, rehabilitation monitoring, athlete performance evaluation, training optimization, and so on.

2.2 Bioeletric sensors

There are a wide variety of physiological signals in the human body, including signals of the brain, heart, muscles, electrodermal activity, and so on. Bioelectric sensors are designed to detect and measure these electrical signals generated by the human body and associated with the previously mentioned activities. The electrical signals captured by the sensors can be used to monitor and analyze different functions in human body. In the subsequent parts, we will explain these sensors and their potential application scenarios.

2.2.1 Acoustic sensors. The acoustic sensor, also known as the microphone, is the sensor that detects sound waves and converts them into electrical signals. It is designed to capture and measure acoustic vibrations in the surrounding environment. Wearables like smartwatches, smart headphones, and

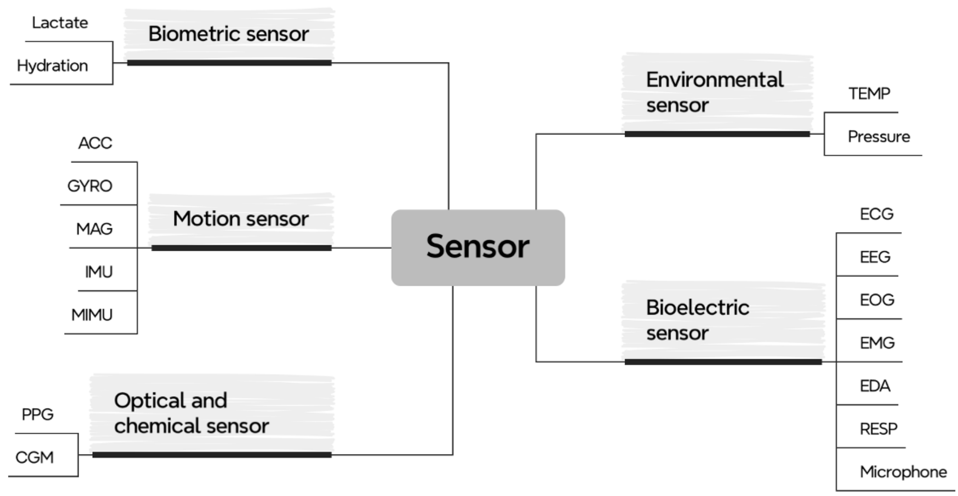

Fig. 3. Wearable sensors used in health and sports

smart gloves usually have built-in acoustic sensors. These integrated sensors enable voice commands, call handling, and audio recording [24, 25].

2.2.2 Electrocardiography (ECG) Sensors. ECG sensors typically consist of electrodes that can record the electrical heart signals and produce a visual representation of the heart's rhythm and activity. The detection of heart electrical signals by ECG sensors makes it a powerful tool for diagnosing and treating cardiovascular diseases such as heart failure, arrhythmia, atrial fibrillation, and so on. Since heart abnormalities are usually asymptomatic and sudden, the ECG sensor needs to be wearable and long-term real-time monitoring, prompting the emergence of some smartshirts and wristbands integrated with the ECG sensor.

2.2.3 Electroencephalography (EEG) sensors. The human brain produces different brain signals all the time, and the response of EEG signals to emotional state fluctuations is sensitive and real-time. EEG wearable sensors usually decode the brain's neural activity through head-mounted brain-computer interface sensors. Still, this head-mounted device is usually cumbersome and not suitable for long-term daily use. Some studies use portable ear-mounted sensors to receive EEG signals [26]. The analysis of EEG signals can help us in the early diagnosis of neurological diseases such as seizures, and stroke. And it also suggests mentally related emotions and diseases. In addition to this, studies have shown that interpreting EEG signals can assist disease rehabilitation through attention control [27, 28], which provides us with insights into the contribution of EEG sensors to limb rehabilitation.

2.2.4 Electrooculography (EOG) sensors. EOG sensors measure the electrical potentials generated by the movement of the eyeball. Electrodes placed around the eyes detect the changes in electrical signals as the eye moves, allowing for the determination of gaze direction [29]. EOG sensors are often used in wearable eye tracking devices.

2.2.5 Electromyography (EMG) sensors. An EMG sensor is a device that measures the electrical activity of muscles. It works by detecting and amplifying the myoelectric signals produced by the

Table 2. Summary of placement of wearable physiological sensors

Type	Location
ACC	Wristband, waistband, smartwatches
CGM	Upper arm, earlobe, or placed on a flat area of the skin with good blood flow, such as the back of the hand and forehead
ECG	Smartshirt, wristband, chestband
EDA	Finger, palm, smart gloves, wristband, smartwatches
sEMG	Placed on any part of the upper and lower extremities with muscles integrated into bandages, wristbands, smartshirt
EEG	Head-mounted, ear-mounted
EOG	Placed around the eyes
GYRO	Wristband, waistband
IMU/MIMU	Wrist, waist, chest, ankle wristband, waistband, smartwatches
MAG	Wristband, waistband
PPG	Wrist, wristband, smartwatches
RESP	Mouth, chest, abdomen.
Pressure sensor	Smart shoes, smart socks, smart gloves
TEMP	Place on the skin surface using adhesive patches or bands
Lactate	Legband
Hydration	Wristband, finger, upper arm, chest
Microphone	Smartwatch, smartglasses, headphone

contraction and relaxation of muscle fibers when the muscles are activated by the nervous system. According to the invasiveness of EMG, it is divided into surface EMG (sEMG) and intramuscular EMG (iEMG). sEMG is usually placed on the skin surface overlying the muscle of interest, typically in a configuration that allows for measurement of the muscles' activity in multiple directions. So it can be placed in multiple places in the body. sEMG positioned around the ankle could detect falls and help the exoskeleton perform better rehabilitation training for patients through accurate estimation of ankle joint torque [30]. sEMG can be deployed at any muscle location in the upper and lower extremities and has various applications [31, 32].

sEMG has many applications in disease prevention, diagnosis, monitoring, and rehabilitation in the medical field. [33] have conducted remote monitoring of muscle diseases through EMG, and Gutierrez et al. [34] provide rehabilitation treatment programs for cervical spinal cord injuries through the muscle signals fed back by sEMG. In the sports domain, it can also be used to monitor athletes' muscle fatigue and evaluate athletes' performance [35].

2.2.6 EDA (Electrodermal Activity) sensors. The EDA sensors, also known as a galvanic skin response (GSR) sensors, usually implemented in the palm or finger, measures the electrical potential difference resulting from changes in sweat gland activity. This indicator reflects the strength of our emotional states and emotional arousal. The close relationship between EDA and human emotions makes it a powerful tool for emotion identification and classification. Due to its property, it's usually used for anxiety monitoring and stress detection [36, 37].

2.2.7 Respiratory (RESP) sensors. Typically, the detection of breathing entails the use of invasive equipment such as breathing masks and mouthpieces, which are often inconvenient for users and cannot provide stable detection over extended periods of time. As a result, numerous non-invasive respiratory sensors have been developed that offer mature and reliable alternatives.

The respiratory inductance plethysmography belt is a well-established RESP sensor for estimating respiration volume by measuring the chest and abdomen movement. It is placed on the user's abdomen or chest and generally contains a conductor that, while being worn by the user, forms a closed-loop circuit. When the user breathes, the inductance also changes, and the breath is detected and measured by monitoring the changed inductance. In addition, there have been other studies that used some research RESP sensors that could have non-invasive measurements of respiration. For example, Kristiansen et al. have used low-cost strain gauge breathing belts to monitor and analyze breathing by converting the mechanical strain (such as the change in belt circumference) generated by tension during the user's breathing process into electrical signals [38]. Filosa et al. analyzed the Fiber Bragg Grating signal to help monitor the breathing process through the corresponding elongating or shortening of the FBG during the expansion or contraction of the chest during the breathing process [39].

2.3 Biometric sensors

Biometric sensors are designed to capture distinct biological or behavioral traits that are unique to each individual. These sensors are utilized to verify identity or monitor specific biometric parameters. For instance, biometric parameters can be derived from human body indicators such as sweat, urine, saliva, and other physiological factors [40–42].

2.3.1 Hydration sensors. Adequate hydration is essential for good health as it supports all body systems. Insufficient hydration can lead to various negative health effects, including headaches, tiredness, and increased thirst. Monitoring hydration levels and assessing water loss is beneficial in multiple situations, such as exercise training or monitoring the status of hospice patients. These methods allow individuals and healthcare professionals to track hydration levels, identify early signs of dehydration, and take appropriate measures to prevent or address it. Common hydration sensors include impedance-based sensors, which estimate hydration by measuring the electrical resistance of body tissues; optical-based sensors, which estimate hydration by analyzing the interaction of light with the skin; and sweat-based sensors, which measure sweat electrolyte concentration. Common hydration sensors utilize optical sensing, which involves analyzing the interaction of light with the skin, and electrical sensing, such as capacitance, conductance, and bioimpedance, to measure and estimate hydration levels [43].

2.3.2 Lactate sensors. Lactate is a byproduct of anaerobic metabolism and is commonly used as an indicator of physical exertion and metabolic stress. Monitoring lactate often requires invasive methods, such as drawing blood, to measure lactate levels. However, advancements in technology have led to the development of non-invasive lactate sensors that can detect lactate through sweat [44]. Non-invasive lactate sensors make use of methods to collect sweat and employ a range of techniques, including enzymatic reactions, biosensors, and spectroscopy, to assess lactate levels in sweat samples.

2.4 Environmental sensors

Compared with bioelectric sensors, environmental sensors are designed to measure the signals of an object or environment, and it does not directly measure biological signals. The response to a physical stimulus or environmental change, such as temperature and pressure, can be converted to an electrical signal by electronic sensors. TEMP and pressure sensors are the common environmental sensors that are used in research.

2.4.1 Temperature (TEMP) sensor. A TEMP sensor measures temperature and converts it to an electrical signal. In the applications of intelligent wearables, TEMP sensors can be used in conjunction with bioelectric sensors to monitor temperature changes in the body during various biological processes or to maintain a constant temperature during experiments or medical procedures. TEMP sensors are essential in our daily life, which have much value in different applications, including medical, industrial, and environmental monitoring. It is often embedded in wearable devices such as smartwatches and smart rings to help people continuously monitor their daily body temperature.

2.4.2 Pressure sensor. Pressure sensors are electronic devices that measure pressure and convert it into electrical signals. It is usually used to measure pressure in the hands and feet to aid in detecting the user's motion analysis. For example, the pressure sensor embedded in the smart insole provides valuable information by analyzing the pressure generated during gait activities. Some are embedded into wearable gloves that grip strength and muscle activity. It has enormous value potential for applications such as gait monitoring, fall detection, and athlete's motion analysis.

2.5 Optical and chemical sensors

Optical sensors use light to detect physiological signals. PPG is a typical optical sensor that uses light to measure changes in blood volume in the microvascular tissue beneath the skin. Then the changes in the light signals provide significant insights about the heart rate, blood pressure, and blood oxygen. For non-invasive continuous glucose monitoring (CGM), some optical CGM sensors use different optical techniques to measure glucose levels. Besides optical-based CGM sensors, chemical-based CGM sensors are also mainstream in this field. For convenience, we categorized PPG and CGM sensors under the 'optical and chemical sensors' category.

2.5.1 Photoplethysmography (PPG) sensors. The PPG sensor is mainly placed on the wrist and integrated into the wristband to detect heart rate, pulse rate, blood oxygen saturation (SpO2), and blood pressure in a non-invasive way. Some are directly attached to the wrists [45], and soles of the feet [46]. Although it is more convenient and comfortable to use than the ECG sensor, the PPG sensor produces strong noise produced by motion artifacts, leading to inaccurate measurement accuracy.

Although PPG has precision limitations, we can still mine hidden valuable information to help us detect and monitor diseases. Such as automatic detection of seizures [47], blood pressure monitoring, sleep apnea, and hypopnea monitoring [48]. One study developed a flexible wearable electronic system to monitor athletes' training performance [49].

2.5.2 Continuous Glucose Monitoring (CGM) sensors. Non-invasive measurement of blood glucose has been an active field. Traditional blood glucose measurement methods usually require pricking a finger with a lancet to obtain a blood sample, which is then analyzed by a blood glucose monitor. This way increases the risk of infection for patients and is extremely inconvenient for patients to use. Many studies have proposed sensors for the non-invasive monitoring of blood glucose, and even though they have not been clinically approved, they still offer great potential for continuous glucose monitoring of blood glucose levels (BGL) [50].

Currently, several mainstream CGM sensors have appeared, including sensors based on optics, microwave, and electrochemistry [51]. Some of them have appeared in the market. For example, C8 MediSensors is an available CGM sensor that uses near-infrared light to measure BGL. GlucoWISE uses radio waves to measure BGL. The released Freestyle LibrePro is based on electrochemistry, which analyzes the electrical signal generated by the electrochemical induction of glucose in the interstitial fluid.

8

Table 3. Sensors in wearable devices

Devices	Sensors	References
Smartwatch Smart wristband	ACC, ECG, IMU, PPG, GYRO, MAG, TEMP, Pressure, Microphone	[55–57]
Smart ring	ECG	[58, 59]
Smart shirt	ECG, EMG, PPG, RESP, TEMP	[53, 60–62]
Smart belt	ACC, IMU, RESP, Pressure	[38, 63–65]
Smart glove	ACC, Camera, IMU, GYRO, Pressure, Microphone	[24, 66]
Vision impairment devices Smart glasses	ACC, IMU, EOG, GYRO, MAG, Camera, Microphone	[29, 67–69]
Smart insole	ACC , GYRO, MAG, TEMP, Pressure	[70–73]
Smart socks	ACC , GYRO, MAG, TEMP, Pressure	[54, 74, 75]
Smart earphone	ACC, EEG, GYRO, IMU, MAG, Microphone	[25, 76]
Smart patch	CGM, ECG, EMG, PPG, TEMP, Biometric sensor	[40, 77, 78]
Smart mouthguard	Biometric sensor	[42, 79, 80]
Rehabilitation devices	IMU	[81, 82]
Fall detection devices	Camera, IMU, ACC, EMG, GYRO, MAG, Pressure	[83, 84]
Tracking system	Camera, IMU	[85, 86]
Sleep monitoring devices	ACC, EOG, ECG, EEG, EDA, EMG, PPG, RESP, IMU, Pressure	[64, 87–90]
Mood monitoring devices	ACC, ECG, EDA, PPG, TEMP, Microphone	[91–93]
Nutrition monitoring devices	CGM, Biometric sensor	[41, 50]

The table includes sensors introduced in the article; other sensors not discussed individually are not listed.

The clinical use of non-invasive BGL testing has been limited despite its accuracy and stability. However, with the aid of ML, it is possible to extract valuable information from the data and enhance the precision of non-invasive BGL measurement, thereby facilitating effective monitoring of BGL levels [52].

2.6 Flexible sensors

Flexible sensors are a type of sensor designed to be stretchable and conform to the shape of the object or the surface they are applied. In our classification standards, we do not consider flexible sensors as a distinct category. Because the term "flexible sensors" predominantly refers to the physical form and adaptability of the sensors, rather than their functional characteristics or the type of data they capture. Therefore, flexible sensors can be designed as EEG, ECG, TEMP, pressure, or other sensors.

Flexible sensors are usually embedded in fabrics, such as smart gloves, smart T-shirts, smart socks and so on. For instance, the clothing fabric incorporates flexible ECG sensors capable of consistently tracking irregularities in heart rhythm [53]. Socks fibers with embedded flexible pressure sensors can continuously monitor foot pressure distribution, allowing early identification of high-pressure points that can lead to ulcers, especially in individuals with diabetics [54]. In summary, the integration of flexible sensors into fabrics is revolutionizing the field of wearables.

2.7 Wearable devices

Each sensor has advantages and limitations, and the information obtained using only one sensor is not comprehensive. On the one hand, a multi-sensor system could provide redundancy and improve the reliability of our data. As an example, it is possible to utilize both PPG sensors and ECG sensors to detect heart rate. By combining the data obtained from these sensors, it is possible to enhance the accuracy and reliability of the Heart rate measurement. On the other hand, different sensors can complement each other. For instance, ACC, ECG, and TEMP sensors could be integrated as a system to classify sleep stages [94]. Similarly, ECG and PPG sensors could be amalgamated to enable automatic seizure detection [47]. Wearable devices are the embodiment of multi-sensor systems. Equipped with a diverse array of sensors, these devices harness the combined benefits of various sensor technologies, enabling them to fulfill a wide range of functionalities and capabilities.

There are a variety of wearables in our real-world life. For example, smartwatches could offer broad functionality about the heart rate, and step taken using the sensors such as ECG and motion sensors [55–57]. Smart glasses provides us the voice command response using acoustic sensors, and can take pictures and record through cameras [29, 67–69]. Moreover, wearable systems exist to track nutritional intake, assess sleep quality, and provide smart tracking among other functionalities. A selection of prominent wearable devices is itemized in Table 3.

3 COMMUNICATION

Beyond the scope of traditional wired sensor transmission, this section predominantly centers on the wireless communication methodologies utilized by wearable devices. Sensor data collection, transmission, and analysis are inseparable from wireless communication technology applications. In this section, our initial focus will be on delineating the fundamental scenarios for the application of wireless communication technology in wearable devices. Following this, we will explore how these scenarios are amalgamated within various network frameworks.

3.1 Communication Scenarios

Bluetooth, cellular networks (3G, 4G LTE, 5G), Wi-Fi, NFC, Zigbee, and LoRaWAN are among the wireless technologies enabling wearables to communicate with other devices or the internet. Bluetooth facilitates short-range communication with other devices, while cellular networks provide broader connectivity options for wearables with SIM cards, allowing direct communication with the cloud or edge servers. Wi-Fi offers high-speed connectivity to local networks and the internet, NFC enables contactless communication, Zigbee is suitable for low-power sensor networks, and LoRaWAN extends the range for applications like asset tracking. These wireless technologies provide flexibility, mobility, and seamless communication for wearables.

Wearable technology encompasses a wide range of devices that can communicate in various scenarios. In the context of wearable communication, several distinct scenarios can be identified. Firstly, device-to-gateway communication involves wearables establishing a connection with a gateway node, enabling access to external networks or services. This scenario often employs short-range wireless technologies such as Bluetooth, Zigbee, Wi-Fi, or NFC to facilitate communication [8]. Secondly, device-to-device communication allows wearables to directly interact with each other, enabling collaborative functionalities or data exchange. Bluetooth, Zigbee, and NFC are commonly employed for device-to-device communication due to their low-power consumption and short-range capabilities [6]. Wearables may communicate with external sensors or peripherals to gather additional data for enhanced functionality. Moreover, wearables can establish communication links with mobile applications running on smartphones, facilitating data exchange, control, and synchronization. Bluetooth, Wi-Fi, and NFC are commonly utilized for device-to-mobile application communication. Additionally, wearables can access and communicate with cloud services, enabling data storage, analysis, and processing. This is achieved through communication methods such as cellular networks, Wi-Fi, Ethernet, MQTT, or CoAP [5, 13]. Lastly, communication with edge computing infrastructure allows wearables to offload data processing and analytics tasks to nearby edge devices. Bluetooth, Zigbee, Wi-Fi, MQTT, and CoAP are often employed for device-to-edge communication [13]. The selection of the communication technologies in each scenario depends

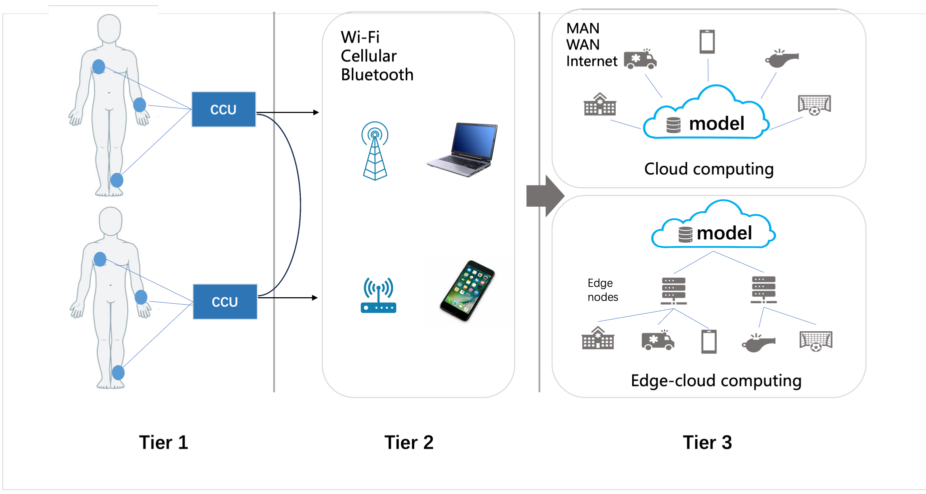

Fig. 4. WBASN communication architecture

on factors such as communication range, data throughput, power consumption, and compatibility with the other wearables.

3.2 Internet of bodies

Building on these communication scenarios, we now delve into specialized network frameworks that embody the integration of these technologies with wearable devices on human body. Innovative advancements in sensors and networks have led to the emergence of new paradigms that redefine our interaction with the world. Internet of Bodies (IoB), fosters a broad, interconnected web of human data collection and exchange [95, 96].

Radio frequency communication such as Bluetooth, Wi-Fi, and Zigbee are the prevalent communication technologies in IoB. But it is susceptible to interference, which could potentially jeopardize the security of human body data, making it vulnerable to eavesdropping. Researchers are increasingly shifting their focus to low power body channel communication, where the human body serves as a medium for the safe transmission of electrical signals. This emerging field of study presents a promising alternative to traditional communication methods for IoB modules [97–99].

3.3 Wireless body area sensor network

IoB extends the IoT paradigm to the human body, it's appropriate to delve into more specific elements within this framework. A critical component within the IoB construct is the Wireless Body Area Sensor Network (WBASN). A WBASN is a collection of multiple wearable sensor nodes, a coordination node that communicates with each other through wireless channels. A WBASN collected and integrated multi-sensor data and then transmitted the data to the cloud for further analysis, enabling various applications in the medical and sports fields [100, 101]. By gathering, transmitting, and analyzing sensor data through WBASN, it is possible to offer remote feedback and assistance to elderly or disabled individuals. Providing remote, online nursing consultations to patients can enhance their quality of life by ensuring timely and personalized healthcare support [102]. Similarly, remote assessments of athletes' performance can be conducted by analyzing their training data, enabling tailored feedback and guidance for optimal outcomes through the WBASN.

Considering the significance of WBASN, our primary emphasis is placed on the architecture and the communication technologies utilized within WBASN, as illustrated in Figure 2. In this discourse, we primarily focus on the three-tier architecture of WBASN, a structure that has been extensively investigated in many scholarly works [103–105]. The three-tier structure includes the intra-BASN, inter-BASN, and beyond-BASN. In addition, we explore two computing frameworks in the architecture, and we also introduce the intricate processes that occur under various circumstances, including sports and healthcare.

3.3.1 Tier1: intra-BASN. In Tier 1, different body-worn sensors, such as motion sensors and physiological sensors, are aggregated into a central control unit, which could be attached to the human body or located in close proximity to the body to ensure efficient communication with the wearable sensors. The CCU acts as the central hub in Tier 1, connecting wearable sensors with external systems and ensuring seamless data transfer and management for remote monitoring. In this tier of communication, the communication range for sensors is limited to several meters within and surrounding the human body for efficient communication. Consequently, low-power, short-range communication technologies, such as Bluetooth, ZigBee, ANT, and Near Field Communication (NFC), are typically employed to facilitate efficient data transmission [103].

3.3.2 Tier2: inter-BASN. Tier 2 includes two types of communication, one is the communication between different body area networks, and the other is the communication between the Central Control Unit (CCU) and the access points or base stations [104]. In specific instances, the CCU stores the collected data and categorizes the traffic into three distinct levels: normal traffic, emergency traffic, and on-demand traffic. This classification is based on the degree of urgency associated with the data. Subsequently, the CCU transmits the information directly to multiple APs or BSs, ensuring efficient communication and data management [105]. The communication technologies employed may encompass cellular networks, wireless local area networks (WLAN), and Bluetooth.

Sometimes CCU is not necessarily required in Tier 2. One study showed that in some systems with fewer sensors, the sensors could process the data locally and communicate directly with a short-range gateway via Bluetooth or ZigBee without the CCU [8].

3.3.3 Tier3: beyound-BASN. Tier 3 involves the transmission of data from the local devices to the cloud or edge devices for computation, often through the internet, metropolitan area networks (MANs), or other wide area networks (WANs). As shown in Figure 2, this level could perform two computing frameworks, including cloud computing or edge computing. Under the cloud computing case, collected data can be stored, processed, and analyzed remotely in the model of the cloud, enabling remote monitoring and data sharing among professionals. The second framework, known as edge-cloud collaborative computing, combines the benefits of both edge and cloud computing to optimize data processing and resource utilization. Data could be transformed and processed both in edge nodes and cloud distributedly.

We now discuss the applications of these two frameworks in two scenarios. In the remote health scenario, using cloud computing, the data is stored in the clinical database in the cloud for medical staff to directly access patient data information or provide emergency medical rescue response. The further combination with the cloud service platform can enable more efficient data management, privacy protection, and data analysis and processing by large models in the cloud [106]. Using edge-cloud collaborative computing, researchers could utilize edge nodes to share part of the computing resources for model inference, which fasts the computing process and save much communication cost. The predictions or estimations were subsequently uploaded to the cloud for storage [107–109]. Medical staff can request patient data according to traffic levels and analyze the data in the cloud to help diagnose and treat patients. Finally, real-time notification is provided to patients. Similarly, athletes can upload real-time training data to the cloud for data storage and analysis in sports training scenarios. Both coaches and athletes can provide feedback for improvement based on data and analytics using cloud computing or edge computing.

4 INTELLIGENT WEARABLES: PRACTICAL APPLICATIONS

Intelligent wearables have significantly contributed to the growth of ubiquitous computing, a concept where computing capabilities are seamlessly integrated into everyday objects and environments. As for a single wearable sensor, ML could be a powerful tool to analyze the data generated by the sensor. In a multi-sensor system, ML plays a pivotal role in improving communication between sensors and fusing information from different sources to make better predictions or decisions.

Overall, the advancement of ML has ushered in a wave of innovative health and sports-related products. For instance, Empatica's Embrace2, a Food and Drug Administration (FDA) approved smartwatch, utilizes advanced ML algorithms to monitor seizures. It is capable of detecting convulsive seizures and then alerting caregivers. Another product, Current Health, is a platform for remote patient monitoring that employs wearables to keep track of a patient's vital signs in real-time. These wearables leverage AI to scrutinize the data and pinpoint potential health threats. In the sports realm, the WHOOP Strap is a wristband that uses AI to keep tabs on athletes' training, recovery, and sleep. Furthermore, the OPTIMEYE S5 lauched by CATAPULT, are employed by numerous professional sports teams globally. They track more than 1,000 data points every second and utilize AI to examine athlete performance and the risk of injury. During the 2022 World Cup in Qatar, a technology called Sports Action Optimization Technology, can work with an IMU in the soccer ball to determine when the ball was kicked and tracked the positions of the last defender and opposing striker. The advent of these products signifies to researchers that the fusion of AI and wearables holds immense potential in the realm of sports and medicine.

To have a more comprehensive and deeper understanding, we conducted a comprehensive search of peer-reviewed literature indexed in the ELSEVIER library, ACM digital library, and IEEE Explore Digital Library using the keywords "wearable device," "machine learning," "health," "sports," or various sensor devices such as "EEG," "ECG" and "IMU," or various ML methods such as "unsupervised," "self-supervised" from 2017 to 2023. Through screening article content and repeat articles, we selected 180 high-quality articles. We have compiled two comprehensive concept maps for both health and sports domains derived from the gathered articles. These maps are presented separately in Figure 5 and Figure 6. The specific categories and the related articles within these maps will be elaborated upon in the ensuing sections.

4.1 Health

As the global population ages and the rapid development of digital technologies, the demand for digital medical care is increasing. Wearables are generating large amounts of information-rich data every day. ML has become a promising data analysis assistant for doctors, helping them efficiently and rapidly diagnose diseases and helping patients recover from diseases. ML also supports clinical decision-making by identifying patterns and anomalies from large amounts of data. In this section, we now mainly illustrate ML applications for wearables from the following four aspects: detection, monitoring, rehabilitation, and personalized medicine. The concept map of the AI-based applications in health is shown in Figure 5, where after each application, relevant references are listed.

4.1.1 Detection. In the medical domain, the diagnosis of disease, especially early diagnosis, is of significant importance to both doctors and patients and saves many medical resources. Since we have multiple sensors that can obtain different physiological signals from the human body, it has

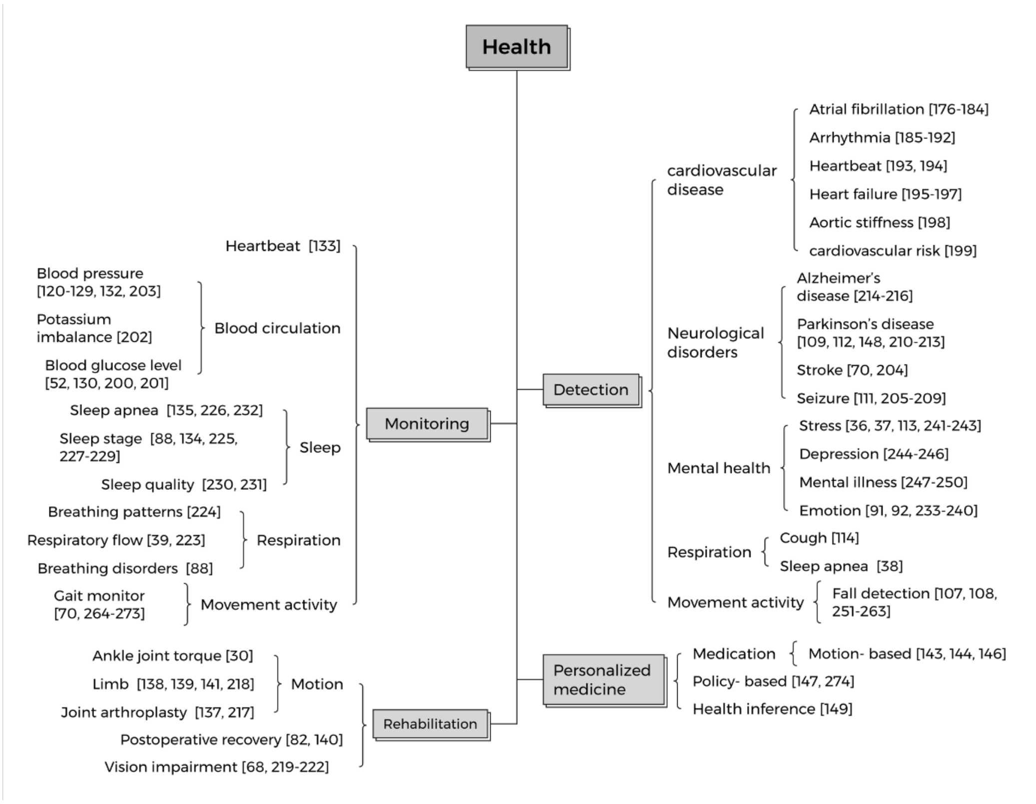

Fig. 5. Health applications using intelligent wearables

huge potential to detect diseases such as cardiovascular diseases, blood circulation diseases, mental disorders, etc. We will discuss possible sensors and potential applications from the perspective of various diseases.

Cardiovascular disease (CVD) detection and monitoring has been an active and promising field since it leads to 17.9 million deaths annually, according to the World Health Organization [110]. As we mentioned in Section 3, ECG and PPG sensors provide a way for people to monitor their cardiovascular health and explore heart activity. ECG sensors measure the heart's electrical activity, while PPG sensors measure the changes in blood, providing continuous monitoring of heart rate and blood oxygen saturation. Many studies tried to apply ML to these two sensor data to diagnose and monitor CVDs, such as atrial fibrillation, arrhythmia, heartbeat abnormality, heart failure, and aortic stiffness.

Another area where wearables and ML are often used to help detection is neurological diseases. This category includes neurodegenerative diseases such as Alzheimer's disease (ADs) and Parkinson's disease (PDs) and some neurological disorders such as stroke and seizures. Due to the close relationship to the human brain, most of the researchers used EEG wearables as a tool to help to analyze these diseases. Rashed et al. utilized a deep convolutional network to analyze the EEG data, enabling the detection of both seizures and their characteristic frequencies simultaneously [111]. In addition, limb and movement disorders also allow motion sensors to be used, such as postural instability of patients with PDs. Sigcha et al. used single waist-worn triaxial ACC to capture the motion signals, which then be used to detect falls of PDs and help to monitor the patients [112].

Detecting emotions is also an important and challenging aspect of understanding human behavior and well-being. Mental states, including happiness, anger, sadness, stress, and depression, are fundamentally associated with human cognitive decision-making and sub-health. Especially in current society, stress and depression are the main topic in current society, which is one of the deterministic factors of an individual's health. Mental states are closely related to the heart and brain, and our skin will also have a certain reaction under tension. So some studies used data obtained from EEG, ECG, or EDA sensors to identify and classify human mental states. Dai et al. utilized multimodal sensor data, including EEG, TEMP, and pressure signals to recognize daily emotion [92]. Garg et al. used a chest-worn device to collect multiple sensor data ECG, EDA, EMG, TEMP, and RESP to train an ML model which helps to detect stress [113].

Detection for health should be in everyday life. From the daily healthcare perspective, the future of human beings is dedicated to living in an ambient assisted living (AAL) environment that saves medical resources and improves life quality with the help of IoE, especially for some elderly and disabled who need the most daily care, such as fall detection, vision impairment. Correspondingly, many studies have exploited ML on sensors to help build an AAL environment. These AAL-based studies encompass the following aspects:

First is cough detection. The cough may be an early sign of many respiratory conditions. By using cough as the biomarker, people may have efficient treatment for respiratory conditions. Doddabasappla et al. developed an intelligent method to detect the cough based on ACCs [114]. Another important behavior detection is fall detection. Studies show that between 40% and 60% of falls among the elderly are unwitnessed. And these falls can be severe enough to cause trauma or even death [115]. Consequently, fall detection has emerged as a prominent area of contemporary research. Using motion sensors to detect falls has made been a promising field researched by numerous investigations. Undoubtedly, the detection of CVDs, as previously discussed, has also made a substantial contribution to the development and implementation of AAL environments.

4.1.2 Monitoring. Monitoring is also of much importance and has wide applications in health, especially for remote health. Learned from Section 2, we know that WBASN provides the soil for the development of remote health. Patients could monitor their health in various scenarios in daily life, such as walking, sleeping, and driving. Wearable sensors transmit real-time generated data to cloud or edge servers, then use ML for data analysis. Finally, the feedback will send back to users for health assessment. Doctors could use ML to analyze the data generated by wearable sensors to help diagnose and treat diseases in real time.

For chronic diseases, long-term monitoring is essential for effectively managing diseases, such as CVDs, diabetes, and pulmonary diseases. As it allows healthcare providers to make informed decisions and adjustments by observing the disease process, ultimately leading to a personal management plan for each patient based on their chronic conditions. In order to achieve this, remote health monitoring, facilitated by wearables, enables the continuous assessment of an individual's physiological parameters and well-being from a distance. As for CVDs, we could have wearable textiles, ear-mounted devices, and head-mounted devices to get real-time ECG data. And then use ML algorithms, such as CNN, which has demonstrated powerful capabilities in ECG signal analysis to help to analyze the data. Utilizing ML, remote health monitoring systems can not only rapidly comprehend and interpret ECG signals but also promptly identify abnormalities that may elude human detection [116, 117].

The well-known chronic diseases hypertension and diabetes both require ongoing monitoring to reduce the risk of some CVDs, and other health problems. The traditional measurement of blood pressure is a sphygmomanometer consisting of an inflatable cuff that is wrapped around the upper arm. The whole process requires to be done by doctors and also be limited by the non-stable accuracy due to different clinical settings. Therefore, it cannot achieve continuous monitoring for patients. So do the traditional diabetes measurements. Commercial blood glucose meters are invasive, requiring a small amount of blood to be obtained by pricking a finger. Wearables are the potential to offer continuous measurements of blood pressure and blood glucose levels. Researchers could use ML to reduce noise and extract valuable information from wearable data. As for higher accuracy, Ahmed and his colleagues combined the CGM wearables and ML methods to evidence the feasibility of continuous monitoring of BGL [52]. In addition, many pieces of research focus on precision improvement. There are numerous precision optimization systems of blood pressure using wearables data proposed [118–129]. Furthermore, for exploring more directions, there are also studies use the wearables data to monitor diabetes [130], the postprandial hyperglycemia [131], and blood pressure classification of ill patients [132].

For the routine monitoring requirements of the general population, the assessment of fundamental physiological parameters, including heart rate, respiratory rate, sleep quality, and gait analysis, holds considerable importance. The observation of these indicators may serve as harbingers of underlying disorders or impending health risks.

Now commercial smartwatches such as Apple watches and Samsung watches use PPG sensors to measure heart rate, but this sensor has a large measurement error due to motion artifacts generated by the sensor's changing contact with skin. So some studies use ML to help PPG artifact removal and enhance heart rate precision. Burrello et al. used the architecture of temporal CNN to estimate the real HR value based on the PPG measurement. They achieved a lower cost to correct and predict HR with a high accuracy rate [133].

Sleep monitoring could diagnose sleep disorders and also provide information on some CVDs and neurological diseases. While the traditional monitoring way, polysomnography, is invasive and expensive. In that case, participants have to sleep in the specific clinical. Wearable sensors make it easy and affordable to monitor sleep at home for normal people. Boe et al. applied an ML model to monitor five different sleep stages based on a wrist-band ACC and three ECG sensor patches [94]. Zhang et al. used wristbands to get the HR and motion signals, then applied a feature extraction and RNN model to learn the classification of sleep stages [134]. In addition to sleep stage recognition, sleep monitoring also includes respiration monitoring. For instance, obstructive sleep apnea (OSA) is a common sleep disorder characterized by episodes of partial or complete cessation of airflow during sleep. This condition poses a significant and potentially insidious threat to health, as it often remains undetected by patients. Jothi and colleagues have employed ML techniques to analyze PPG data, thereby enabling the monitoring of OSA and facilitating its timely identification [135].

Respiratory monitoring does not only occur during sleep. Daily life requires respiratory monitoring. Respiratory rate and pattern can provide valuable information about an individual's overall health status and the presence of health conditions such as asthma and pulmonary disease. Filosa and his colleagues also designed ML algorithms to monitor the daily respiratory flow through wearable data [39]. The respiratory airflow encompasses crucial information as well. Research has demonstrated that the exhaled breath of an infected individual may contain pathogenic aerosols capable of disseminating into the surrounding atmosphere, thereby posing a potential risk for transmission [136]. By monitoring and analyzing aerosols, we may find aerosols as biomarkers and monitor potential diseases and human physical conditions.

Patients with disorders often have an unsteady gait so gait analysis could analyze the balance and coordinates of the gait. But this usually requires long-term monitoring and evaluation, which is very time-consuming and inconvenient for the patient. The emergence of smart insoles, smart socks, and other wearables has led to advancements in gait analysis and guidance. Naturally, ML could use sensor data to improve the gait analysis in multiple disease rehabilitation. Park et al. applied ML to the data obtained from a smart insole (integrated with a pressure sensor, ACC, and GYRO). It enables effective real-time monitoring and gait classification of stroke patients [70].

4.1.3 Rehabilitation. Some disorders, such as PDs, stroke, and arthritis, can make it difficult for the body's upper and lower limbs to move. On the other hand, rehabilitation is lengthy and requires patient care from medical staff. Based on these problems, we now introduce the ML and wearables application in the rehabilitation process.

the most common recovery application is limb rehabilitation. Especially for some patients who need careful care and restore their limbs after the surgery. Ramkumar et al. developed a platform that can monitor the rehabilitation of patients using the smartphone and motion sensors after the knee arthroplasty [137]. Lee et al. propose an ML-based method to help the rehabilitation in activities of daily living of stroke patients [138]. Ernesto et al. used ACC to track the upper-limb motor recovery of patients with stroke or a traumatic brain injury and ML analysis for recovery intervention for patients [139].

In addition to recovery of limbs, general postoperative recovery except limbs can also be monitored with different wearables. For example, Zhang et al. used smart wristbands to monitor pancreatic surgical patients' conditions and then utilized ML to analyze the wristband data to predict the post-operative complications [82]. Counci et al. also utilized smartwatches to help assess patients' recovery outcomes in hospitals [140].

Intelligent wearable systems have promoted the development of exoskeletons for various limb rehabilitation. Some studies use wearables to translate patients' recovery intentions into signals, which are then analyzed using ML algorithms. Based on the analysis, the exoskeleton robot will receive instructions for continuous movements that can aid in the patient's recovery process [141]. To produce continuous instructions, studies tried to estimate continuous numerals. Zhang et al. used an EMG-driven ML model to estimate the ankle joint torque that can help the patient's recovery [30]. Liu et al. designed a human-machine interaction system based on sEMG, which ML algorithms analyze to identify human motion intentions [142].

4.1.4 Personalized medicine. First, from the human point of view, personalized treatment always consumes medical resources and cannot find a satisfactory solution because different doctors' and patients' feedback and preferences are considered. So digital health provides us with a way to make personalized medication management. Second, from the system perspective, with the population of personalized medicine in the future, the sensor network between patients will become more complex. So networks with low energy and high-efficiency transmission are more conducive to personalized medicine.

Patients frequently struggle to adhere to their medication regimen due to a variety of factors, such as a lack of understanding, mistrust of healthcare providers, or simply forgetting to take their medication as prescribed. The main aim of medication inference is to optimize therapeutic strategies by tailoring prescriptions to each patient's unique needs and circumstances. Therefore, some studies tried to explore intelligent wearables that could achieve medication adherence. These studies are mainly divided into two aspects: motion-based and policy-based. Motion-based methods usually use motion sensors to detect if the patients are taking the pills. Cheon et al. used ML to learn the smartwatches data that can detect the patients' low medication state [143]. There are other researches using motion sensors to evidence the action of taking medicine [144–146]. The other is policy-based studies, which are based on the data provided by wearables to make personalized medicine management for patients, that is, to propose personalized drug dosage and time use deep reinforcement learning [147, 148].

In addition to medication intervention, ML can also perform different end-to-end interventions on the patient's health status based on the wearable data [149].

4.2 Sports

ML has a wide range of applications in sports to evaluate athlete performance, prevent injuries, and propose training improvements [150]. But these ML applications are generally based on optical cameras. Studies have used cameras to capture motion information and then use ML to analyze the captured video to make interpretable assessments of athletes' movements [151]. But these camera-based methods are unsuitable for some outdoor sports places because the venue is too large, and the video may have some occluded motion. Some studies used professional equipment, such as an isokinetic dynamometer, to get the dataset. But this way requires athletes to conduct off-filed additional tests under professional equipment, rather than on-field real-time sports data of athletes [152]. Based on these limitations, wearables provide a way to get real-time data without venue limitations and expert guidance.

In this part, we will mainly introduce three aspects that wearables could be integrated with ML in sports science: sports analytics, injury prevention, and physiological variables prediction. And the corresponding concept categories are presented in the concept map in Figure 6.

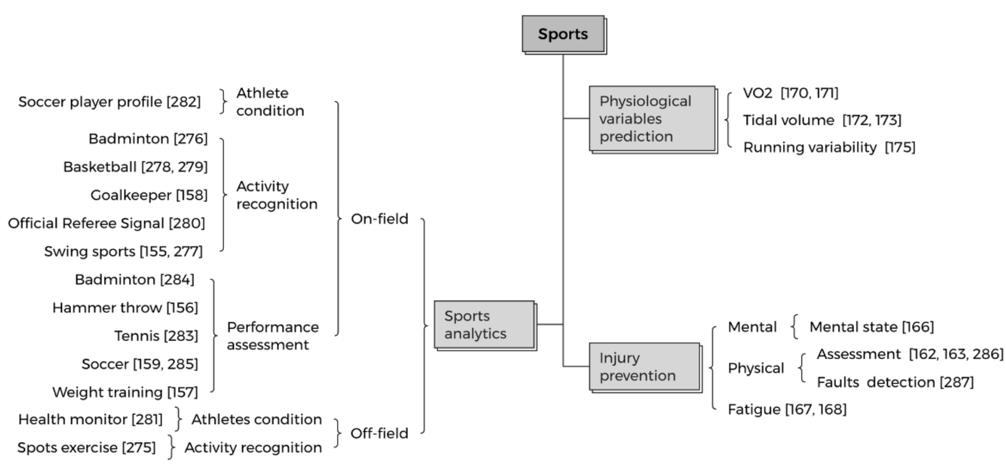

Fig. 6. Sports science applications using intelligent wearables

4.2.1 *Sports analytics.*

Sports analytics represents a critical domain for both coaches and athletes. They can analyze the data during the competitions or training stage to evaluate the athletes' physical fitness, performance evaluation, and improvement of training strategies. 'On-field' means the performance occurs during an actual game, while 'Off-field' means the performance occurs outside of the competition.

The most common and popular on-field application is sports activity recognition. In the majority of athletic pursuits, the assessment of body posture and limb coordination serves as a proficient means of acquiring motion-related data. Through feedback on postures, coaches can adjust athletes for more efficient training and, at the same time, prevent athletes from being injured [153, 154]. The development of motion sensors allows us to more sensitively and accurately capture the movement information of athletes, even some minor movements that are not easy to be observed by the naked eye. So many studies use motion sensors to recognize sports activities. Anand et al. developed an ML-based method to effectively classify shots using data generated by motion sensors in swing sports [155].

Evaluating body posture and limb coordination can also contribute to the appraisal of athletic performance. At times, the feedback provided by referees can be influenced by subjective opinions and inherent biases, potentially leading to less objective assessments of performance. ML can avoid such mistakes and provide objective feedback on the motion assessment of sensor data. Wang et al. designed a wireless wearable device integrated with ML that can provide real-time biomechanical feedback [156]. Kowsar et al. developed an unsupervised ML-based wearable device Liftsmart which could track and analyze weight training exercises in real-time [157].

Sports activity recognition can also be achieved off-field. Haladjian et al. harnessed wearable data to construct an ML model that operates as a virtual referee for goalkeeper trainees during the training phase. Then goalkeeper could recognize the activity and get feedback to foster skill development [158].

Apart from analyzing sports activities and performances, it is equally crucial to assess the athletes' physical condition. As it enables coaches and support staff to assess performance, identify potential health concerns, and optimize training regimens. Wang et al. applied ML on the wearable data and designed a system that can continuously monitor the health of sportspersons [32]. From the athlete's personalization aspect, analyzing the athletes' conditions helps to get an explainable profile for each specific player. Lisca et al. learned insights from a single motion sensor by the ML model to get an explainable prediction of the goalkeeper. They found different motion components of a specific goalkeeper could have different explainable results, which provide a way for others to manage personalized training plans [159].

4.2.2 Injury prevention. Athletes injury prevention is important both for the athlete and the team. For example, physical injuries in football players can be costly to both the player and the team. One study found that in the 2016-2017 season, Premier League injury-related wage bills £9m per team for a season [160]. Moreover, addressing and preventing mental health issues among athletes is also of vital importance, as these concerns can significantly impact their sleep and overall performance. A study showed that early psychological intervention has positive therapeutic effects in athletes [161]. Based on these two directions, we will introduce the studies that used Intelligent wearables to prevent physical and mental injury.

As mentioned, the referee's judgment is biased and limited. ML can usually provide more objective and timely feedback to prevent body injuries using some motion sensors. Rossi et al. used the GPS composed of IMU sensors to measure the personal training data of football players and then used these data to train an ML model to predict the players' injuries [162]. Tedesco et al. also used an IMU sensor to capture the motion information. The generated data was used for training an injury classifier using ML models (KNN, NB, SVM, XGB, MLP) [163]. In addition to a motion sensor, muscle signals also provide a way to assess the injury. The sEMG sensor was used by Dai et al. to predict the muscle fatigue of volleyball players. They applied an ML model on the sEMG sensor data to evaluate muscle fatigue into three levels [164].

Athletes' mental health is often overlooked but plays an important role in athlete performance. The majority of studies have used psychological stress questionnaires to screen athletes with initial mental problems. However, this method depends on the subjective answers of athletes, and it cannot avoid missing some early athletes who really have mental problems [165]. Wearables can effectively and accurately collect physiological data without being subject to the subjective influence of athletes and can be used as a better basis for analysis. However, there are very few studies in this area. Melentev et al. applied the ML models on EEG data to detect the tiredness of the eSports players [166].

Fatigue increases the risk of injury during games of athletes, as the tired muscles are more prone to strain and other injuries. So, fatigue prediction provides feedback for both coaches and athletes to adjust the training strategy. IMU sensor data was used by OP and his colleagues to develop an ML model that predicts the rating of perceived exertion, a validated subjective measure of fatigue [167]. In addition to real-time fatigue prediction during sports, Jiang et al. used a temporal ML model to predict future fatigue by analyzing the IMU sensor data [168].

4.2.3 Physiological variables prediction. The measurement of an athlete's physiological parameters has a significant impact on the athlete's training plan and preparation. And that usually requires the help of a kinesiologist measurement. For kinesiologists, measuring and judging some physiological parameters is time-consuming and expensive, and they cannot avoid being influenced by subjective and empirical factors. Based on real data, ML can quantify data into objective scores based on continuous learning. The combination of ML and wearable could assist the kinesiologist's judgment and predict higher accurate physiological variables. Based on the related literature, we have VO2, tidal volume, and running variability that could be explored and predicted by wearable data using ML.

VO2 is an important physical index for athletes. Represents an individual's body's ability to inhale, deliver and transport oxygen. Accurate measurement of VO2 can help athletes guide their training, but this usually requires expensive professional equipment. The measurement process is invasive and needs to be completed under the supervision of professional personnel. Although wearable smartwatches on the market can measure VO2, they are limited by the low accuracy and cannot measure instantaneous VO2 in real-time [169]. Some research applied ML models to affordable wearable devices to get easy-to-obtain parameters such as heart rate, breathing frequency, and minute ventilation to predict accurate instantaneous VO2. Shandhi et al. used a built wearable patch placed on the mid-sternum to collect seismocardiography (SCG), ECG, and pressure signals. Later, they trained the ML models to predict the instantaneous VO2 based on the multi-sensor fusion data [170]. Amelard et al. collected some RIP data by the smart shirt and trained a temporal ML model to predict the VO2 [171].

Tidal volume is another important variable of respiratory function and is a measure of the difference in the amount of air that is inhaled or exhaled in a single breath during normal breathing. In the sports field, tidal is a significant measure of respiratory function. Thus, it provides valuable signs about an athlete's aerobic capacity and endurance. Traditional methods usually use mathematical methods to predict tidal volume, which is restricted to the data pattern. So, some studies use ML to predict the tidal volume based on wearable data. Hurtado et al. collected respiratory data through the RESP belt and applied the data to the ML model to predict the tidal volume [172]. Soliman et al. extracted features from the ECG and SCG signals with an ML model to help predict the tidal volume [173].

Moreover, existing research on the variability and fluctuation of the running is usually done by professional kinesiologists to reveal the fluctuation characteristics of complex time series data [174]. Although the existing standard is to use mathematical models to analyze variability, one research has begun to explore ML-based methods, which proposed the use of an ML model to analyze the data obtained based on the IMU sensor to estimate running variability [175].

5 METHODOLOGIES

As AI technology evolves, traditional statistical methods are being complemented by an increasing number of ML-based techniques in wearables applications. ML is an important branch of AI, which can learn from data and automatically optimize its own system without human intervention. The utilization of ML models for data analysis enables decision-makers to unearth concealed patterns and regularities within the dataset. By processing the available information, ML algorithms facilitate the generation of future predictions and provide valuable insights to inform decision-making processes. ML mainly falls into four primary categories: supervised ML, unsupervised ML, semi-supervised ML, and reinforcement learning (RL).

In an effort to provide deeper insights to researchers regarding the application of ML algorithms in intelligent wearables, we conduct a comprehensive examination of various ML methodologies, drawing upon the literature discussed in Section 3. Primarily, we elucidate four distinct categories of ML, along with the prevalent ML models utilized in these applications. The categories of ML and their corresponding models are detailed in Table 4 (for Health applications) and Table 5 (for Sports applications). In the subsequent section, we shed light on the diverse ML techniques' application in the fields of sports and health, demonstrating how they can bring value to these domains.

5.1 Supervised learning

The most popular category is supervised learning, which is a method of training models with labeled data. Supervised learning learns a mapping function between inputs variables and corresponding outputs through labeled training data. Usually, the model uses a cost function to measure the gap between the model output and the true output. Then the model automatically adjusts and updates internal parameters through this feedback to reduce the cost.

There are two main categories in supervised learning: classification and regression. Classification predicts class category labels, while regression predicts continuous variables. For instance, consider the prediction of sleep stages. In classification, we can categorize sleep stages into discrete categories (e.g., awake, light sleep, deep sleep) based on brain wave patterns and other physiological signals. The model learns to classify each period of sleep into these categories. On the other hand, regression could be used to predict a continuous quantity related to sleep, such as the precise duration of each sleep stage. It seeks to fit the actual duration of each sleep stage as closely as possible.

A wide variety of classification models are commonly employed in supervised learning, including Decision Tree (DT), Support Vector Machines (SVM), Support Vector Regression (SVR), K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Gradient Boosting algorithms (GT) such as eXtreme Gradient Boosting (XGBoost), AdaBoost (Adaptive Boosting), Naive Bayes (NB), and several types of Neural Networks like Multilayer Perceptrons (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and transformer. Given the limited space available, we do not elaborate on these models. Our purpose is to give readers a more high-level idea of how to abstract the specific problems of intelligent wearables into different ML applications.

As for the classification problem such as the disease classification, and sleep classification. A popular approach is to directly apply one of the classification models like SVM and KNN, for classifying electrical signals. Nevertheless, some techniques consider the temporal characteristics of 1-D electrical signals (e.g. CGM, ECG signals), and employ temporal models such as Temporal Convolutional Networks (TCN), causal networks, RNNs, and transformers for classification tasks. Additionally, some researchers transform 1-D signals into 2-D signals for further analysis. For instance, Liu et al. converted the original 1-D electrical signals into 2-D spectrograms, facilitating the use of CNNs and other models for training [186]. In addition, numerous studies employ the strategy of running multiple ML models concurrently and then utilizing ensemble methods to derive the most optimal results. This approach takes advantage of the strengths of various models and mitigates individual model weaknesses.

Table 4. Application of intelligent data analysis in health

Category	Applications	Count	Supervised	Un-supervised	Semi-supervised	Rein-forcement	Sensors& Devices	Approach
Cardiovascular	Atrial fibrillation detection	9	[176–183]		[184]		ECG, PPG	RF, CNN, SVM, KNN, RNN, BiLSTM
	Arrhythmia detection	8	[185–190]	[191]	[192]		ECG,PPG	CNN, SNN, BiLSTM, VIT
	Heartbeat detection and monitoring	3	[133]	[193]		[194]	ECG,PPG	CNN, TCN, Causal-CNN, MLP, model-basde RL
	Heart failure	3	[195, 196]	[197]			ECG	RF, SVM, KNN, RF, EBT, U-Net, Word2Vec
	Other cardiovascular disease detection	2	[198]		[199]		ECG, PPG	XGBoost, CNN, BiLSTM
Blood circulatory system	Blood glucose levels	4	[52, 130, 200]		[201]		CGM, EDA, PPG, TEMP, Smartwatch, Smartphone	MLP, RF, SVR, SVM, KNN, Clustering
	Blood disease classification	1	[202]				PPG	XGBoost
	Blood pressure estimation	12	[120–129, 132]		[203]		ECG, PPG	CNN, TCN, U-Net, GRU, LSTM
Neurological disorders	Stroke detection	2	[70, 204]				ACC, ECG, Smart insole	SVM, RF
	Seizures detection	6	[111, 205, 206]		[207–209]		ACC, ECG, EEG, Smart insole	CNN, RNN, LR, XGBoost, BiL-STM, VAE
	Parkinson's disease detection	7	[109, 112, 148, 210–212]	[213]			ACC, MAG, IMU, GYRO	KNN, SVM, CNN, KNN, transformer, RF, NB, DA, XGBoost, DT
	Alzheimer's disease detection	3	[214–216]				EEG	DNN, DT, NB, KNN, SVM, RF, MLP, GBDT
Rehabilitation	Motion	8	[30, 82, 137–140]	[217]		[218]	GYRO, IMU, EMG, Smartwatch, Smartphone	MLP, LR, RF, SVM, K-means, Q-learning
	Vision impairment	5	[68, 219–222]				Smart glasses, camera, smartphone	Transformer, YOLO, CNN
Respiration	Respiration monitoring	5	[39, 88, 223, 224]				ECG, EMG, IMU, PPG, RESP, Smart ring	LSTM, KNN, CNN
	Cough	1	[114]				ACC	CNN
Sleep	Sleep monitor	11	[38, 88, 134, 135, 225–230]	[231, 232]			PPG, EDA, EEG, ECG, IMU, RESP, Smart ring, Smartwatch	RF, MLP, RNN, KNN, NB, SVM, LDA, QDA, CNN

Table 4. Application of intelligent wearable data analysis in health (Continued)

Category	Applications	Count	Supervised	Un-supervised	Semi-supervised	Rein-forcement	Sensors	Approach
Mental health	Emotion detection and classification	9	[92, 233–235]	[91, 236–240]			ACC, ECG, EDA, EEG, PPG, Smartwatch, Microphone	SVM, RF, XGBoost, CNN, Clustering, Transformer, K-means
	Stress detection	6	[36, 37, 113, 241, 242]		[243]		ECG, EDA, EMG, PPG, RESP, TEMP	AdaBoost, KNN, LR, RF, SVM, CNN
	Depression detection	3	[244–246]				ACC, IMU, Smartphone, Smartring	SVM, CNN, RF, KNN, LR
	Mental illness detection	4	[247–250]				ACC, EEG, Smartwatch, Smartphone	CNN, KNN, XGBoost
Movement and activity	Fall detection	15	[107, 108, 251–262]		[263]		ACC, MAG, GYRO, IMU, ECG, Smartwatch, Smartphone	RNN, LR, NB, RF, SVM, KNN, CNN, DNN, MLP
	Gait monitoring	12	[264–271]	[70, 266, 272]	[273]		IMU, ECG, ACC, Smart insole, pressure sensor	SVM, KNN, CNN, LSTM, HMM
Medical system	Medication adherence	5	[143, 144, 146]			[147, 274]	Smartwatch, ACC, GYRO, IMU	LR, MLP, CNN, Policy-based RL
	Health inference	1				[149]	ACC	CNN

Similarly, in regression problems, related research also uses one model or model ensemble methods to obtain optimal results. Whether it is a classification or regression when dealing with situations characterized by large volumes of data or high data complexity, deep learning is often the go-to approach. CNN-based models such as ResNet and U-Net, are particularly prevalent in these scenarios due to their effectiveness and versatility.

In different application fields of health and sports, both classification and regression are indispensable and are flexibly applied to different scenarios. Classification serves as a prevalent approach in numerous applications, including diagnosing illnesses, identifying driver fatigue, among other uses. For example, in the case of early diagnosis of PDs, multiple neurologists would need to mark the severity ratings of the patients in the data set, and this labeled data would be used to train a supervised learning model [210]. However, in some scenarios, regression models are more suitable. For example, ML converts the human cognitive recovery processes into command signals to control the movement of the exoskeleton. Because the motion of bones and joints is continuous, the signal output by ML should also be continuous. In this case, they use the sensor data to generate continuous output signals, which are treated as the labels for the supervised learning model [141].

5.2 Unsupervised learning

In many cases, labeling data is cumbersome and time-consuming, and the categories of some data are even unknown. Hence the emergence of unsupervised learning, in which the model can find and classify some patterns in unlabeled data sets. Different from supervised learning, unsupervised learning has no label and cost function. The input of the model includes unlabeled data and a set of

Table 5. Application of intelligent wearable data analysis in sports

Category	Applications	Count	Supervised	Un-supervised	Semi-supervised	Sensors	Approach
Sports analytics	Sports activities recognition	8	[155, 158, 275–279]		[280]	IMU, smart insole	CNN, BiLSTM, SVM, NB, RF, DT, LDA, QDA, KNN
	Athlete condition monitoring	2	[281, 282]			IMU, smart-watch	RBM, NB
	Performance assessment	6	[156, 159, 283–285]	[157]		IMU	DNN, XGBoost, CNN, DT, NB, AdaBoost, RF, SVM, KNN
Injury prevention	Physical injury prevention	4	[162, 163, 286]			IMU, pressure sensor	DT, KNN, NB, SVM, MLP, XGBoost, LR
	Mental injury prevention	1	[166]			EEG	RF, GBT
	Faults detection	1	[287]			IMU	SVM, DT, KNN, MLP
	Fatigue prediction	2	[167, 168]			IMU	GBT, MLP, LR
Physiological variables prediction	Oxygen uptake prediction	2	[170, 171]			RESP, ECG, SCG, Pressure sensor	XGBoost, TCN
	Tidal volume prediction	2	[172, 173]			ECG, RESP	SVR, LR, RF
	Running variability	1	[175]			IMU	CNN

observations, and the model's goal is to learn hidden patterns through the mapping of inputs to observations.

Unsupervised learning algorithms usually include clustering, dimensionality reduction, and association. Clustering means putting similar features of data together as a category, such as K-means and hierarchical clustering. Dimensionality reduction could reduce the dimensions of the features while retaining the necessary information as much as possible. Principal component analysis (PCA), singular value decomposition (SVD), and linear discriminant analysis (LDA) are the common dimensionality reduction methods. The association aims to identify relationships between variables in large datasets. Through our survey of the literature, it's evident that clustering is widely applied in various domains. This method of identifying and grouping similar data points can yield valuable insights, especially when dealing with large or complex datasets. It's an essential tool for exploratory data analysis, enabling the discovery of hidden structures and relationships within the data.

Unlabeled data is ubiquitous in many fields, including medicine, where large quantities of data are often collected without explicit labels. This makes unsupervised learning techniques particularly useful for analyzing medical data and discovering patterns and relationships that can aid in diagnosis, treatment, and drug discovery. Yeche et al. used unsupervised learning to monitor patients in Intensive Care Units (ICU) online based on the time-series data [288]. For example, Kowsar et al. proposed the first smart wearable device based on unsupervised learning, which can provide real-time feedback and evaluation of the performance of weightlifters [157].

5.3 Semi-supervised learning

Semi-supervised learning is between supervised and unsupervised learning, which combines both labeled and unlabeled data to improve the model. Semi-supervised learning typically involves using a smaller amount of labeled data in combination with a much larger amount of unlabeled data to train a model. The idea is that the additional unlabeled data can help the model learn a better representation of the underlying structure of the data. Semi-supervised learning employs a variety of techniques such as self-training, autoencoder, model titillation, etc. From Tables 4 and 5, an encoder-decoder structure is most popular used in the related semi-supervised setting papers [192, 199, 207, 208, 280]. In this setting, the encoder learns a compressed representation from the labeled data, and the decoder generates new data instances from this representation. For example, the ECG is not easily available most of the time. Mohebbian and his colleagues developed a generative model based on CNNs. They constructed a CNN-based autoencoder, where the encoder was trained on data from 47 labeled participants. The decoder was then finetuned using data from an additional 26 unlabeled participants [192]. Besides, Samyoun et al. used an encoder to extract meaningful features from the input data, so that the model serves as an additional input representation that can improve the performance [243]. Qu et al. utilized the CNN-based teacher-student setup which is popular in model distillation to classify the gait in the semi-supervised learning way [263]. Mikos et al. utilized the self-training way, where the model uses its predictions on the unlabeled data to generate pseudo-labels, treating them as if they were true labels [273].

5.4 Reinforcement learning

RL has no labels but with less supervision. It performs the optimal actions of agents with the aim of maximizing the reward from the observations it gleaned from interacting with the environment. The model constantly modifies itself based on feedback. So, RL is suitable for people to find the optimal policy in an uncertain environment with continuous trial and error between the agent and the environment. RL can be broadly categorized into three key approaches: Value-Based RL, where the goal here is to find the optimal value function, which is the expected return for each state or state-action pair. The agent uses this function to decide the best actions to take. Examples include Q-learning and Deep Q-Network (DQN). Model-based RL involves an agent acquiring knowledge about the environment by constructing a model, which is subsequently utilized to make informed decisions for future actions. This can be more sample-efficient but often requires more complex algorithms and computation. Policy-based RL, where the agent learns a policy function directly from the state and action pairs it experiences.

Based on the gathered literature, researchers commonly employ RL techniques to customize treatment plans for diseases [147] and to model and analyze musculoskeletal movements in patients [218].

6 CHALLENGES

Intelligent wearable devices have shown tremendous potential for human future life. The use of ML in wearable devices can enhance their capabilities for data analysis and enable more personalized insights into user behaviors across various fields. However, the development of these technologies must be carefully balanced with challenges that arise from both the user and wearable device perspectives. In this section, we delve into potential challenges from three distinct perspectives: those related to wearable devices, technological considerations, and user-associated issues.

6.1 Wearable devices

6.1.1 Ergonomics. Wearables need to conform to the human body and accommodate natural movements comfortably. Achieving a design that fits well and avoids discomfort can be challenging.

6.1.2 Size. Users often favor lightweight, compact devices for comfort and convenience. But as wearables become smaller and more compact, maintaining high functionality and performance becomes challenging due to limited space, heat dissipation issues, and integration difficulties.

6.1.3 Manufacturing and cost. Wearables need to be durable and able to withstand everyday use, including exposure to moisture, impact, and wear. Ensuring quality materials, robust construction, and rigorous testing can increase manufacturing costs. The size of wearable devices can also impact the manufacturing process and associated costs. Smaller devices may require more intricate manufacturing techniques and assembly processes, which can increase production expenses.

6.1.4 Battery technology. Users often favor lightweight, compact devices for comfort and convenience, but this limits the size and life of the battery. Thus, achieving high energy density in small form factors is challenging.

6.1.5 Optimization. The advanced capabilities of the wearables such as continuous data processing, sensor operations, and inter-device communications demand high power, leading to faster battery drain. Thus, optimizing these operations to be power-efficient is an ongoing challenge.

6.1.6 Storage. Wearable devices often require quick access to data to provide real-time feedback or enable interactive functionalities. However, devices with larger capacities may have slower read and write speeds, resulting in delays in data access and response times. Balancing storage capacity with data access speed is challenging.

6.2 Technology

6.2.1 High-quality data availability. Despite the significant progress made in the development of wearable devices, challenges about data quality persist [289]. These challenges include noise, missing data, motion artifacts, and electromagnetic interference, which may arise due to hardware or software issues with the sensors or data transmission. In addition, user behavior during physical activity can also introduce noise and artifacts, further complicating the acquisition of high-quality wearable sensor data [290].

6.2.2 Information fusion. In addition, in multi-sensor systems, data acquisition is more challenging. As discussed previously, using multi-sensor systems can enhance the capture of activity information compared to single sensor data acquisition. However, the integration of data from multiple sensors presents unique challenges. These challenges arise due to differences in sensing modalities, sampling rates, and data formats between sensors, which hinder the screening and integration of high-quality data [291].

6.2.3 Model reliability. Many powerful ML models rely on large amounts of high-quality training data. But at some point, the derived models are biased or have low accuracy due to limited data. Some models misinterpret data due to overfitting. Although the model can never achieve 100% accuracy, we still need to improve the model's reliability constantly. In the pursuit of future advancements, the implementation of reliable and applicable models presents challenges. As the complexity of models increases, it becomes crucial to strike a balance between sophistication and practical usability while maintaining generalizability to accommodate the specific needs of different fields.

6.2.4 Interpretability. ML-based wearables face challenges in interpretability due to the complexity and black box nature of most of ML models. This is particularly crucial in medical and sports applications, where having a standardized explanation plan can facilitate decision-making for doctors and coaches.

6.2.5 Real-time communication. Due to the limitations of sensor storage memory and computing, a large amount of data generated usually needs to be transmitted to edge nodes or the cloud for computing. In some scenarios, real-time or near real-time data feedback is particularly important, such as the emergency of some cardiac patients [292] and the real-time performance feedback of athletes on the field [23]. However, these could be challenging due to various factors, including network congestion, packet loss, and signal interference. High latency can compromise the reliability and effectiveness of wearable devices in healthcare and sports.

6.2.6 Individual difference. Each person has unique characteristics, including their health status, fitness level, lifestyle habits, and even the way they wear and interact with the device. These differences can greatly affect the performance of ML algorithms, which may have been trained on population-level data and may not account for nuances at the individual level. Even for a single individual, many factors can change over time. Aging, changes in health status, variations in lifestyle and activity levels, and even changes in the way the person wears the device, all can affect the device's data and, consequently, the performance of the ML algorithms.

6.2.7 Compatibility. Wearable devices often need to integrate with other devices, platforms, or ecosystems to provide a comprehensive user experience. Ensuring seamless integration with other smart devices can be challenging due to compatibility issues of different platforms.

6.3 User

6.3.1 Security. Wearables have the potential to offer significant benefits to human beings, but they also introduce security concerns. Especially for medical uses, as these sensors collect and transmit sensitive patient data, they are vulnerable to cyber attacks that may result in catastrophic consequences. For example, malicious hackers may attempt to gain control of wearable medical devices and cause harm to patients [293].

6.3.2 Privacy. One study shows that the de-identification of wearables is not doing a good job of protecting our privacy [294]. Privacy issues stems from the collection of sensitive information by sensors, such as the user's health status, activity location, and other personal data. In some cases, sensors may transmit this information to cloud service providers without adequate protective measures in place, potentially exposing users to privacy breaches. Furthermore, some sensors may also collect information about the user's surrounding environment, which can further exacerbate privacy concerns [295]. Ensuring user privacy is a significant challenge that developers must address to maintain trust and promote responsible AI development.

6.3.3 Informed Consent Complexity. Obtaining informed consent from users is a fundamental ethical principle. However, communicating complex data practices, potential risks, and implications to users in a clear and understandable manner can be challenging. Because users usually don't have a genuine understanding of the data they are sharing.

6.3.4 User acceptance. Although the wearables technology is constantly evolving and updating, user acceptance is an important issue to consider. In a study conducted in France involving 1,183 chronic disease patients, it was found that 35% of these patients would decline a treatment recommendation made through a wearable device [296]. User acceptance of wearable sensors depends on a variety of factors, including comfort of use, cost, invasiveness, operational complexity, data privacy, and other considerations. As the user base continues to expand, it is a big challenge for wearables to strike a good balance between user experience acceptance and device effectiveness.

7 OPPORTUNITIES

Contemporary wearables are becoming seamlessly integrated into human lifestyles, so it's important to consider the development of ML-based wearables in this field. In thi s section, we aim to offer an in-depth exploration of the potentialities encompassed by AI applications within the realm of wearable technologies.

7.1 Intelligent wearables

7.1.1 Sensing mechanism. The future of smart devices lies not just in their ability to collect data but also in their capacity to gather more specialized and professional health indicators. For example, the non-invasive detection of blood sugar allows users to get professional health indicators without leaving home. However, the sensing capabilities of these sensors are not yet sufficient for clinical use, and it is essential to improve their sensing functions and measurement accuracy [297].

7.1.2 Battery. Advances in extended battery life and energy-efficient design are particularly important for related commercial equipment. For example, although the Apple Watch can measure users' ECG data, HR, fitness tracking, and sleep stages, it often causes headaches due to its battery consumption.

7.1.3 User-friendly design. User-friendly designs include accessible design, ensuring the technology is usable and beneficial to everyone, including people with disabilities. User-friendly designs such as voice recognition and tactile feedback are increasingly needed.

7.2 Integration of wearables with IoT

7.2.1 Real-time communication. As the proliferation of diverse devices continues, it becomes imperative to ensure seamless communication between smart wearables and other IoT devices. This seamless interconnectivity is crucial to deliver personalized user experiences.

7.2.2 Privacy and security. As we increasingly rely on cloud-based data models for user data analysis, issues related to privacy breaches and security vulnerabilities become prevalent. To mitigate these issues, strategies such as data anonymization, data encryption, and differential privacy are often employed. Moreover, edge computing is gaining significant traction in the present scenario. A popular approach in this context is federated learning, where the model is dispatched to the edge device holding the data and is trained locally. This approach ensures that only model updates are relayed back to the central server, not the actual user data.

7.3 Improvement of ML algorithms

7.3.1 Denoising. Wearables continuously amass an extensive array of data, thereby necessitating the deployment of meticulous data processing methodologies. A critical preliminary step in this procedure is denoising. While this task can be accomplished via conventional data processing methods, ML techniques present a promising prospect for efficacious noise elimination. These techniques include methods such as time-series anomaly detection and noise forecasting.

7.3.2 Annotation. Simultaneously, the manual annotation of the copious data derived from these devices is not only labor-intensive but also imposes substantial time demands. As a result, the scope for unsupervised learning in this domain is considerable, given its ability to effectively harness the unlabeled data generated in real time.

7.3.3 Model refinement. Refining the model structure, algorithm, and real-time parameter estimation is pivotal to maximizing the utility and value derived from wearables.

7.4 Interdisciplinary application: Health

7.4.1 Personalized medicine. The domain of biomedicine and health presents vast potential for personalized medical practices, including comprehensive patient care, management of elderly individuals' daily routines, and more. Wearables could access and combine diverse models to create a personalized user profile. This profile facilitates the recording and analysis of individuals for informed health planning.

7.4.2 Disease detection and monitoring. Such capabilities are particularly critical for managing chronic diseases and long-term health, improving the quality of life significantly. Moreover, the early detection of diseases, such as cancer, can be facilitated by these devices, which greatly benefits patients and medical staff and saves the cost of care [298, 299].

7.4.3 Cadiorespirory fitness for athletes. Numerous research endeavors have focused on aiding patients in detecting and diagnosing cardiopulmonary diseases [176, 177, 185–189, 195–199]. However, limited attention has been directed towards facilitating athletes in identifying indicators of cardiopulmonary health. These indicators encompass crucial parameters like maximum oxygen uptake, minute ventilation, and tidal volume. Acquiring such measurements typically necessitates the utilization of costly specialized equipment and trained professionals. Nevertheless, the widespread availability and accessibility of everyday wearable devices, such as smartwatches and mobile phones, hold substantial potential for enabling real-time monitoring of these data by athletes.

7.5 Interdisciplinary application: Sports

7.5.1 Mental health. In the evolving landscape of sports science, the future promises the realization of multidimensional applications of wearables. These devices play a crucial role not only in the physical well-being of individuals, but they also contribute significantly to mental health promotion. While there has been research on using wearables to predict mood states for normal people, there is a strong need for more studies that focus specifically on athletes. Unlike other groups, the emotions of the athlete group will be reflected in their usual training and competition. They may experience different emotional challenges from normal people, such as performance anxiety, training pressure, and the desire to win [300].

7.5.2 Virtual coaches. In addition, like specific personal management in public health, we can also use sensor data to analyze athletes' own physical conditions and sports performance to develop specialized virtual coaches. The virtual coaches could provide explainable recognition of sports activities or performance evaluations. For example, explaining the contribution ratio of specific actions to sports performance in a specific sport is more conducive to how coaches and students improve training and competition.

7.6 Digital twins

Digital twins refer to the virtual representation or simulation of an individual's physiological and behavioral characteristics [301]. These simulations are crafted from data harvested through wearables, capturing information such as biometric parameters, sleep patterns, and more. The digital twin is capable of gathering multimodal longitudinal data, which facilitates personalized plans for individuals.

7.6.1 Health. In the healthcare sector, digital twins play a crucial role in both routine care and disease diagnosis. For everyday care, digital twins can track and analyze an individual's data and lifestyle habits remotely, enabling the prediction of potential health issues. When it comes to disease diagnosis, digital twins can create a model based on the patient's specific disease characteristics and personal information. This allows for the development of a tailored treatment strategy for the patient and provides insights into possible disease progression. Digital twins also find utility in various facets of healthcare such as disease diagnosis, pharmaceutical development, trauma management, among others [301].

7.6.2 Sports. Similarly, digital twins have great potential in the sports field. Digital twins can help athletes optimize their performance by simulating different training strategies and predicting outcomes [302]. And it can also help athletes to manage the fitness activities through data recorded by wearable devices (e.g. food income, activity, sleep) [303]. In the realm of team sports, digital twins can emulate matches, aiding coaches and athletes in formulating superior strategies. They have the capacity to dissect the tactics of opposition teams, anticipate the results of specified game strategies.

8 PESTEL ANALYSIS

In the subsequent section, we will delve into a comprehensive analysis of the intelligent wearables industry by employing the PESTEL framework. The PESTEL model provides a comprehensive framework for evaluating the multitude of external factors that influence the deployment of intelligent wearables. It assists in navigating the complexities of government regulations, policies, and political stability, enabling stakeholders to identify and meet the necessary legal and industry-specific standards. Economically, the PESTEL model helps assess market trends, consumer purchasing power, and economic indicators that could impact the deployment of intelligent wearables. From a social perspective, it aids in understanding societal attitudes, health consciousness, and demographic factors that can influence the use of these wearables. From a technological perspective, it helps to gauge the pace of technological innovation that can affect the development and adoption of intelligent wearables. Environmentally, the PESTEL model assists in examining the environmental impact of the production, use, and disposal of intelligent wearables. From a legal perspective, the PESTEL model promotes an understanding of the ethical implications associated with the use of intelligent wearables, such as maintaining data privacy, security, and respecting user autonomy. Subsequently, our discussion will encompass these dimensions.

8.1 Political factors

Intelligent wearables should both consider the policies related to wearables and the policies of AI research development. Those policies vary depending on different countries and regions. Regarding wearables regulation, for instance, the FDA in the United States oversees only those wearables that are classified as medical devices under the Federal Food, Drug, and Cosmetic Act. Most of the wearables do not fall under FDA regulation [304]. But in order to make consumers more confident in the protection and accuracy of user data privacy, some manufacturers seek FDA approval for a specific feature of their device, like Apple gaining FDA clearance for ECG monitoring and irregular heart rhythm monitoring. Regarding AI regulations, for instance, The European Union proposed a comprehensive legal framework for AI in 2021, known as the AI Act. The regulation regulates AI by conducting a risk assessment of AI and is constantly improving as AI develops [305].

However, there are still many countries that do not have mature regulations. But with the rapid development of AI and wearables, more countries and regions will participate in making regulations. Consequently, understanding and navigating these regional regulations is crucial for AI developers, businesses, and policymakers to ensure compliance, promote responsible AI development, and foster trust in AI systems among users.

8.2 Economic factors

The economic factors influencing intelligent wearable systems in health and sports present both opportunities and challenges. Growing demand for remote patient monitoring and fitness trackers is driving market projections, supported by declining device costs through technological advances. Venture funding is targeting customized health and performance-boosting solutions. However, while affordable access remains a challenge, payment models integrating with insurers can help realize the potential of therapeutic devices. At an individual level, economic stability impacts discretionary wellness spending using innovative trackers. Regulatory programs stimulating digital healthcare adoption, from rehabilitation to injury prevention, can expand provisions across global populations. Cloud-based services and data platforms offer new commercialization prospects. Indeed, a balanced approach leveraging standardized and tailored offerings may be required to optimize benefits for users across varying economic capabilities. Ongoing innovation has the potential to further minimize costs and maximize clinical values.

8.3 Social factors

Societal attitudes, demographics and cultural norms play an important role in influencing the adoption of intelligent wearables. From a health and wellness perspective, rising health consciousness is supporting demand for wearables that enable proactive healthcare monitoring and fitness tracking to facilitate active lifestyles. From a demographics perspective, the aging population and younger tech-native generations present opportunities for remote patient monitoring, assistive care devices and physical activity trackers. Vulnerable groups like the elderly, pregnant women and children could particularly benefit from wearables tailored for their needs. Notably, professionals in healthcare and sports industries have specific needs for efficiency gains through work-focused wearables.

Another important aspect is the social wealth distribution, where the adoption varies based on income levels, with wealthier regions and populations viewing wearables more as a personal care luxury. Developed countries tend to pursue high-quality wearables for daily wellness support. Cultural Acceptability plays a considerable role, where attitudes differ based on cultural context regarding the form and functionality of wearables. Diverse groups may require tailored solutions that consider cultural preferences and expectations. It is also important to take into the consideration, the privacy, security, and trust aspects. User comfort levels depend on companies adequately addressing data concerns and demonstrating responsible practices for sensitive information collection. Overall, intelligent wearables must account for varied social factors influencing their adoption potential across global population segments, industries and regions to maximize benefits. Standardized as well as tailored solutions may be needed.

8.4 Technological factors

Technological innovation can profoundly shape the development and adoption of intelligent wearables. Advancements in areas such as miniaturized sensor technology, network connectivity, computational power, and data analytics can significantly impact this industry. Miniaturization of sensors through technologies like printed and flexible electronics have enabled novel form factors for wearables like smart tattoos and textiles. Small, powerful sensors allow for expanded health and activity monitoring capabilities. Continuous improvements in short-range communication protocols like Bluetooth help ensure reliable data transmission from devices. Integration of different wearables and other IoE devices through technologies like low-power wide-area networks provides opportunities for real-time multi-device data analysis and sharing. This leads to more convenient data management for users and data-driven insights. Additionally, advancements in energy efficiency are pushing the development of low-power wearables forward. Innovations around energy harvesting, ultra-low power chipsets and optimized protocols enhance battery life, sustainability and the user experience of continuously-worn devices. Growth of edge and cloud computing infrastructure supports processing and analyzing large volumes of IoT data, including datasets from wearables. Emerging techniques in ML and data mining unlock deeper insights. Technologies like 5G and augmented/virtual reality also present opportunities for new application areas. However, frequent iterative updates can introduce issues of compatibility, integration and product obsolescence if not properly managed. Ensuring interconnectivity between generations requires adherence to standardization. Substantial R&D investments are also needed to continuously develop new capabilities in this fast-paced environment. Overall, the rapid technological evolution presents both opportunities to innovate new wearable products and services, as well as risks of sustainability if stakeholders are unable to effectively manage change. Continuous adaptation will be crucial for intelligent wearables to remain relevant in this dynamic ecosystem.

8.5 Environmental factors

As for wearables manufacturing, wearables are typically constructed from diverse materials, encompassing plastics, metals, and textiles. Such materials, however, can pose significant environmental challenges, with plastics, in particular, manifesting a substantial environmental impact due to their non-biodegradable nature and their capacity to remain in the environment for extended periods. To ameliorate the environmental impact of wearables, a number of measures have been proposed, including the use of sustainable materials such as recycled metals and organic textiles. By incorporating such materials into wearable device design and production, manufacturers can help reduce the environmental impact of their products while simultaneously meeting the growing demand for environmentally friendly technological solutions.

Additionally, wearables may serve as a valuable tool to facilitate the development of a sustainable environment. For instance, intelligent wearables can be utilized to monitor air and water quality to prevent the release of pollutants and safeguard the quality of our daily environment.

8.6 Legal factors

Intelligent wearables developers should be aware of the potential legal disputes and liabilities that can arise to ensure the products' rigorous testing and quality control. Specifically, developers must take steps to safeguard the product's patent and ensure that customers' rights and interests are protected. If a user is injured due to wearing a sensor or if sensitive data of a sensor user is leaked, the developer should be obligated to provide relevant compensation. In some contexts, intelligent wearables collect a variety of user data that could potentially be used for discriminatory purposes. For example, during health monitoring, some health data may be used by insurance companies or employers in a discriminatory manner against individuals. Therefore, users should be fully aware of the type of data the device is collecting, how the data will be used, who will have access to it, and how long it will be stored before using the wearables. At the same time, users have the right to withdraw their consent at any time. Many countries have data protection laws, especially for sensitive data about humans. For example, the Illinois Biometric Information Privacy Act in the U.S. requires explicit consent from individuals before their biometric data can be collected. Violations of these types of laws can lead to significant legal penalties. Moreover, developers must be required to compensate users if the device provides inaccurate predictions that significantly influence the user's decision-making. Especially for some scenarios, the prediction error may lead to a fatal impact on decision-making. More importantly, developers must consider industry-specific regulations, such as FDA regulations in the United States, which are significant in shaping the wearables.

9 CONCLUSION

This survey provides guidelines for researchers interested in intelligent wearable applications, from novice to experienced. We thoroughly review four critical areas: sensor technology, medical and sports applications, ML algorithms, and sensor networks. We also discuss opportunities and challenges around techniques as well as societal factors. Using the PESTEL framework, we analyze external factors impacting the intelligent wearables industry, offering a holistic understanding of the current landscape. Overall, our survey covers relevant knowledge in health and sports, presenting a well-organized synthesis useful for researchers, practitioners, and stakeholders.

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