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Review

Wearable Sensors for Vital Signs Measurement: A Survey

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Abstract: With the outbreak of coronavirus disease-2019 (COVID-19) worldwide, developments in the medical field have aroused concerns within society. As science and technology develop, wearable medical sensors have become the main means of medical data acquisition. To analyze the intelligent development status of wearable medical sensors, the current work classifies and prospects the application status and functions of wireless communication wearable medical sensors, based on human physiological data acquisition in the medical field. By understanding its working principles, data acquisition modes and action modes, the work chiefly analyzes the application of wearable medical sensors in vascular infarction, respiratory intensity, body temperature, blood oxygen concentration, and sleep detection, and reflects the key role of wearable medical sensors in human physiological data acquisition. Further exploration and prospecting are made by investigating the improvement of information security performance of wearable medical sensors, the improvement of biological adaptability and biodegradability of new materials, and the integration of wearable medical sensors and intelligence-assisted rehabilitation. The research expects to provide a reference for the intelligent development of wearable medical sensors and real-time monitoring of human health in the follow-up medical field.

Keywords: wearable medical sensors; vascular embolism monitoring; IoT security; medical sensor networks; medical sensor robots; medical sensor rehabilitation assistance

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1. Introduction

With the rapid development of science and technology, the process of urbanization is accelerating, and the construction of smart cities is now on the agenda. The construction of smart cities is closely related to transportation, medical treatment, economy, culture, and tourism in the city. With the global spread of coronavirus disease-2019 (COVID-19), people paid particular attention to their health. Thus, the development of the medical field has become of the utmost priority. In traditional medicine, the use of stethoscopes, thermometers and electrocardiographs has played a great role in human health monitoring and diagnosis. However, with the development of sensor technology and Artificial Intelligence (AI) technology, intelligent performance within the medical field has also greatly improved, such as the intelligent monitoring of patients' blood pressure, wearable sensors or implanted medical sensors to monitor vital signs, etc. [1,2]. Therefore, the application and intelligent development of medical sensors have become the focus of scientific research scholars in related fields.

In the process of intelligent development in the medical field, sensors are an effective way to acquire data. For example, in the process of human breathing detection, a thermal element is placed under the nose. During breathing, the temperature change of the airflow exhaled from the nose causes the resistance of the thermistor to change, thereby causing the voltage to change; subsequently, the waveform of the breathing state is obtained after amplification and filtering [3]. However, if the sensor only relies on the thermal element, although the device is relatively simple, it is susceptible to the influence of external temperature changes, which may cause misjudgment. Therefore, the more reliable thermistor airflow method can be used. In a medical infusion monitoring system, the capacitive liquid level sensor detection method is used to measure the infusion liquid level [4]. When the height of the liquid level in the infusion bottle changes, the proportion of air contained in the medium between the two plates of the capacitor changes accordingly, which eventually causes the size of the capacitor to also change, thereby reflecting the change in the remaining amount of liquid medicine. Therefore, an infusion-monitoring sensor can be designed with different specifications according to the volume of different infusion bottles to achieve the result of monitoring the medical infusion. Of course, there are many sensors involved in the medical field, such as photoelectric sensors, ultrasonic sensors, etc., which combine massive Machine Type Communication (mMTC) with the medical system network to achieve human health monitoring [5,6].

In the application process of a medical sensor system, the wearable medical sensor studied here uses mMTC technology to continuously and accurately transmit, in a timely manner, the normal physiological activity information of the human body in the natural environment to the medical data center through the network, which is convenient for doctors to observe the patient's condition. For example, vital sign parameters collected by wearable or implanted sensors are collected by receivers (such as mobile phones and computers), and the collected parameters can be used for preliminary data analysis [7,8]. Moreover, depending on the analysis results indicating the physiological condition of the testee, and when it is judged that the physiological condition is abnormal, the guardian will be notified. Finally, the records are transmitted to the medical platform data center via 5th Generation Mobile Communication Technology, where the data can be stored and further analyzed. In addition, large-scale machine communication technology not only reflects the connections in terms of equipment scale, but also has the advantages of efficient network overheads and reliability. By using sensor technology to coordinate the transmission of collected data, not only can the patient's vital signs be effectively monitored, but it also helps the patient receive the care of medical staff more quickly [9]. For example, a remote patient health monitoring system and emergency medical response system have extremely important practical significance in the care of the elderly and the monitoring of chronic diseases.

Therefore, continuous remote monitoring of vital signs in clinical or family environments is of great practical significance to improve the understanding of patients' vital signs. The current work chiefly analyzes the application of wearable medical sensors based on wireless communication technology in vascular infarction, respiratory intensity, body temperature, blood oxygen concentration and sleep detection, which reflects the key role of wearable medical sensors in human physiological data acquisition. Additionally, further exploration and prospecting are made by considering improvements in the information security performance of wearable medical sensors, enhancing the biological adaptability and biodegradability of new materials, and integrating wearable medical sensors and intelligent-assisted rehabilitation. This work is expected to provide a reference for the intelligent development of wearable devices and real-time monitoring of human health in the medical field.

The overall structure of the work is as follows:

Section 1 defines the background, current situation, and research significance of wearable medical sensors.

Section 2 classifies wearable medical sensors, focusing on the application of wearable medical sensors in vascular infarction, respiratory intensity, body temperature, blood oxygen concentration, sleep detection, and so on.

Section 3 looks forward to the intelligent prospect of wearable medical sensors, such as information security improvement of wearable medical sensors and material improvement, and their application in intelligent rehabilitation assistance.

Section 4 summarizes the research results and expounds the follow-up research direction.

2. Classification of Wearable Medical Sensors

As a key module of medical data collection in the medical field, medical sensors assume crucial tasks in the actual application process. In terms of module components, a wearable medical sensor has a similar structure to the traditional intelligent medical information system, usually including a processor module, sensor module, wireless RF module, and a capability supply module. To further improve the versatility, modularity, assembly, and other advantages of wearable medical sensors, the processor module, sensor module, and wireless RF module are often compatible, and the collected data are connected to the platform by the nodes existing in the wearable medical sensors. Of course, if the wearable medical sensor fails or needs maintenance, only the sensor module would be updated, so as to achieve the rapid increase of the database type and, finally, effectively complete the scalability and maintainability in the sensor node.

2.1. Classification Method of Wearable Medical Sensors

With the rapid development of science and technology, the application of sensors is becoming more intelligent. In the medical field, wearable medical sensors can convert chemical cost and concentration into electrical signals by using the principles of biological electrodes, physical changes and chemical reactions, to finally achieve data acquisition. Additionally, these sensors can selectively identify biochemical substances to achieve the effect of non-electrical parameters. Human data can be obtained from wearable medical sensors through implanted sensors, "temporary" insertion sensors, external sensors, and external sensors in contact with body fluids. The most important characteristics of implantable sensors are their small size, light weight, low power consumption, compatibility with the body, and stability, in that they will not decay over time. For example, the micro piezoelectric thin-film vibration sensor in blood vessels is helpful for cardiac pacing. "Temporary" insertion sensors are inserted into the body through an incision, such as catheterization. Such sensors, for example the silicon micromechanical pressure sensor to help shrink, is generally used for several minutes to several hours. An external sensor is mainly used to monitor the physiological parameters of the human body by connecting the electrode part to the outside of the skin. Sensors in contact with body fluids are usually used in vitro. For example, disposable blood pressure sensors are mainly used in surgery and intensive care, so they can continuously monitor the patient's blood pressure.

In addition, unlike mechanical sensors, wearable sensors usually use photoelectric effects, biological impedance principles, or thermal sensing elements to measure vital signs and bioelectric activities. Biochemical sensors combine chemical sensitive layers and transducers to convert chemical or biological signal molecules into electrical signals, thus quantifying biological indicators, such as glucose, alcohol, and electrolytes. In clinical practice, physiological signals of concern include electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), electrooculogram (EOG), phonocardiogram (PCG), photoplethysmography (PPG), and ballistocardiograph (BCG); electrodermal activity (EDA) can often be combined with inertial measurement unit signals that characterize the patient's posture and body movement [10–17]. Table 1 presents the monitoring characteristics, relevant technical parameters, and a summary of research into relevant fields of clinical application of wearable medical sensors.

Furthermore, depending on the different functions of the wearable medical sensors, they can be divided into wearable medical sensors for detecting vascular infarction, respiratory intensity, body temperature, blood oxygen concentration, and sleep. Their specific classification is shown in Figure 1. The application analysis is emphasized according to its different effects.

Table 1. Summary of monitoring characteristics, relevant technical parameters, and clinical application of wearable medical sensors.

Scholars	Monitoring Signal	Channels	Signal Frequency/Hz	Acquisition Frequency/Hz	Signal Amplitude/mV	Record Duration	Clinical Application
Zhuo et al. [10]	ECG	1–12	0.05–150	250–1000	0.1–5	10 s–24 h	Heart disease monitoring, heartbeat classification, emotion recognition, sleep staging
Razjouyan et al. [11]	EEG	1–256	0.1–100	0.3–3000	0.1–100	0.5–24 h	Brain disease monitoring, emotion recognition, sleep staging, motion recognition, brain function detection
Jayarathna et al. [12]	EMG	1–32	25–5000	512–10,000	0.1–100	30 s–24 h	State recognition
Wang and Lin [13]	EOG	1–4	0.1–20	200	0.05–3.5	0.5–24 h	Sleep staging
Yun et al. [14]	PCG	1	10–400	1–2000	−2–2	0.5 s–24 h	Heart disease monitoring, heartbeat classification, emotion recognition, sleep staging.
Akbulut et al. [15]	PPG	1	0.25–40	5–500	−10–10	100 s–24 h	Heartbeat classification and sleep staging
Frerichs et al. [16]	BCG	3	1–20	1–20	−0.05–0.05	5 s–24 h	Heart disease monitoring, heartbeat classification, emotion recognition, sleep staging
Izmailova et al. [17]	EDA	1	0.1–16	16–128		110 s–24 h	Emotion recognition

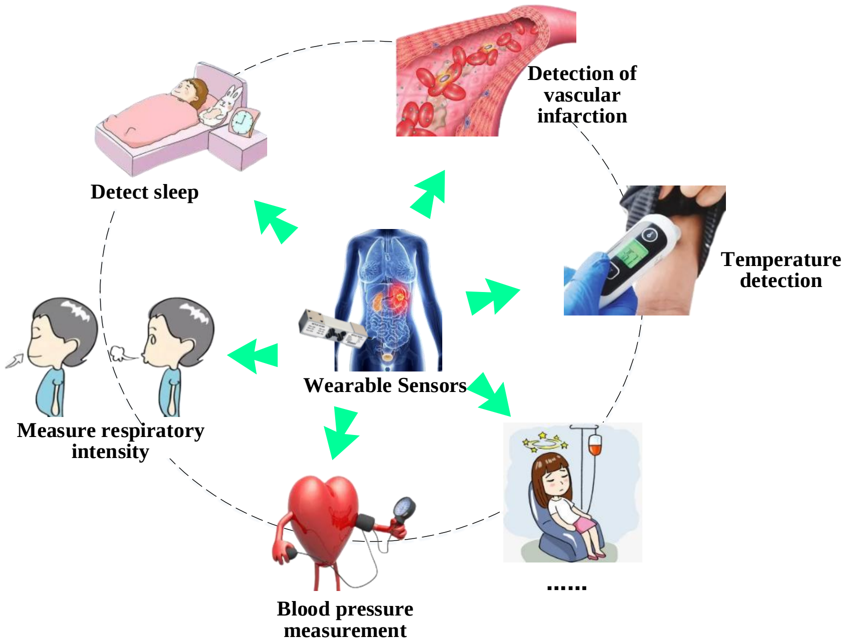

Figure 1. Schematic diagram of different application classification of wearable medical sensors.

2.2. *Classification and Application of Wearable Medical Sensors*

Wearable medical sensors are classified according to their application; they acquire different organ or physiological parameters from the human body, such as respiratory physiological parameters, blood pressure physiological parameters, body temperature physiological parameters, and sleep physiological parameters. They are very important for knowing the vital signs and health in people's daily life [18]. The specific classification applications are as elaborated below.

2.2.1. Wearable Medical Sensors for Detecting Vascular Infarction

The symptoms of vascular embolism mainly include atherosclerosis, diabetes, hyperlipidemia, hypertension and other causes, and it mostly occurs in elderly people over sixty years old. Wearable sensors are expected to realize active personal health management, better treatment of various medical conditions, and better monitoring of health, mental, and activity statuses of the elderly [19]. At the same time, there are many classifications of vascular embolism, such as cerebral vascular embolism, intestinal vascular embolism, pulmonary vascular embolism, and prostate vascular embolism. Therefore, in the detection of vascular embolism diseases, different tests will be carried out according to the patient's symptoms. Many research scholars have conducted research in this area; Lv et al. (2013) used sensors and interactive visualization technology to visually analyze the molecules, cells and organs in the human body, so that medical workers could complete detection in the human body in a short time, so as to achieve a detection effect [20]. Petani et al. (2020) integrated an ozone sensor into medical and biological analysis equipment so that the dissolved ozone concentration of human body fluids and tissues, such as blood, could be measured on-site during medical procedures. It was found that significant progress can be made in measuring temperature, range, and response and recovery times [21].

While reviewing the above-mentioned research, vascular embolism of the cardio-cerebral blood vessel was found to be a related research topic. However, there are few studies on the relatively rare vascular embolism diseases, such as lower extremity arterial embolism, mesenteric embolism and uterine arterial embolism. Therefore, the application direction of medical sensor research now includes different types of vascular embolism diseases.

2.2.2. Wearable Medical Sensors for Detecting Breathing Intensity

The human body has two ways of breathing, namely through the nose and through the mouth. When the human body breathes, the temperature and pressure under the nose change with the passage of the breathing airflow. Therefore, the breathing state of the human body can be obtained by detecting changes in pressure and temperature. Many scholars have conducted research on the detection of respiratory intensity (Table 2). Fan et al. (2018) designed a respiration measurement device based on a portable pressure sensor. A new algorithm based on the BP (back propagation) neural network was also proposed to stabilize device calibration and eliminate pressure signal noise. Finally, through experimental evaluation and case studies, the results showed that under appropriate parameter settings, the proposed BP neural network (BPNN) algorithm can effectively improve the reliability of the newly designed breathing device [22]. Presti et al. (2019) discussed the manufacture of a flexible sensor, based on fiber grating encapsulated in Dragon skin 20 silicone rubber. They developed a wearable breathing and heart rate monitoring system and conducted an experimental evaluation of the sensor's response to strain, temperature changes, and relative humidity changes. The results showed that the system was easy to wear, non-invasive, and elastic, and it seemed to be suitable for matching the chest wall displacement well. It is used to monitor FR and HR, which provides the possibility of detecting respiratory intensity [23]. Zhang et al. (2019) designed a new type of fiber optic sensor that uses a mesh microbeam to simultaneously measure the heart rate (HR) and respiratory rate (RR) of infants during the perioperative period. The feasibility of the mesh microbend fiber sensor was evaluated, and the sensor was placed under the subject. The research results showed that the proposed microbending optical fiber sensor had good consistency with the standard physiological monitoring results used in the current medical environment when measuring HR and RR [24]. Tao et al. (2020) studied the detection effect of respiratory intensity by using a medical sensor with a three-dimensional tetrapodal ZnO micro-structured networks (T-ZnO MNs) material spin-coated on an aluminum foil/ZnO piezoelectric film SAW (surface acoustic wave) device under ultraviolet light irradiation and relative humidity stimulation. they demonstrated that the sensitivity of the prepared material to UV (ultraviolet) light intensity changes significantly under the bending condition. At the same time, after using T-ZnO MNs, the sensing performance of the respiratory characteristics increased by nearly 1.7 times, showing its ability to enhance the effect of respiration and respiration monitoring applications [25]. Miripour et al. (2020) designed a simple electrochemical sensor to selectively detect the intensity of ROS (reactive oxygen species) in sputum samples (volume less than 500 µL) in response to the new coronavirus epidemic. The results showed the accuracy and sensitivity of the response calibration to both be 97%, which provides hope for real-time tracking of the new coronavirus in sputum samples based on reactive oxygen species in more than four hospitals [26].

Table 2. Review of different scholars' research on respiratory intensity monitoring by wearable medical sensor.

Scholars	Sensor Types	Wearable Medical Sensor Model	Effect
Fan et al. (2018) [22]	Pressure sensor	BPNN-based respiratory measurement device	It effectively improved the reliability of the newly designed respiratory device.
Presti et al. (2019) [23]	Flexible sensor	Wearable respiratory and HR monitoring system	It is suitable for matching chest wall displacement and can be used to monitor FR and HR.
Zhang et al. (2019) [24]	Optical fiber sensor	HR detection model of perioperative infants based on new optical fiber sensor	It was consistent with the standard physiological monitoring results.
Tao et al. (2020) [25]	Piezoelectric film sensor	Respiratory monitor based on piezoelectric thin-film sensor	The sensitivity of respiratory characteristics was improved by nearly 1.7 times.
Miripour et al. (2020) [26]	Electrochemical sensor	The strength of ROS (reactive oxygen species) was used to detect sputum samples selectively (volume less than 500 µL) during COVID-19	The accuracy and sensitivity of response calibration was 97%.

However, in the actual breathing-intensity detection process, the air pressure changes in the nose and mouth caused by breathing are very weak, and the sensitivity of the air pressure sensor is often very high, making it more susceptible to the influence of external factors, and resulting in misjudgment [27,28]. Therefore, this research proposed an algorithm for detecting breathing state and frequency, based on changes in temperature and humidity, as shown in Figure 2. After the algorithm is processed, the temperature and humidity changes in the breath can be successfully transformed into changes in the breathing state. This method is simple to implement, using a digital wearable medical sensor, and avoiding the need to filter and amplify analog signals related to temperature and humidity caused by the use of analog sensors to isolate DC processing. The difference in the digital wearable medical sensor data change is used to replace the average value extraction used in the previous analog circuit, and the enlarged design simplifies the apnea detection circuit. Perhaps, in the future, some occupations, such as pilots, can use wearable respiratory-intensity sensors to continuously monitor their physiological state. Even sooner, drivers will be able to use wearable respiratory-intensity sensors to undergo alcohol testing before driving, so that traffic accidents caused by drunk driving can be avoided.

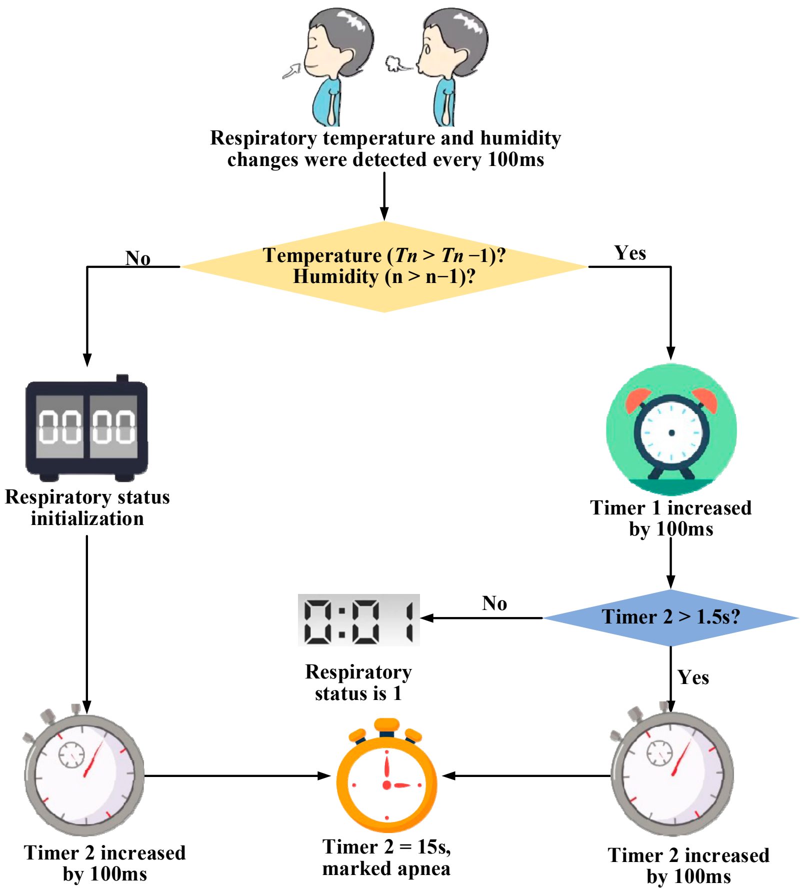

Figure 2. Flow chart of medical sensor algorithm for detecting respiratory status and frequency, based on changes in temperature and humidity.

Figure 2 shows the specific steps of the algorithm flow. First, the latest eight temperature and humidity sampling points are taken at the current sampling time each time and cached in the array. Second, the difference between the temperature and humidity between every two adjacent sampling points in the array is measured to obtain the difference between the adjacent temperature and humidity sampling points. Third, with further sampling, the array that saves adjacent differences is constantly updated. At this point, the array can be processed in real time to calculate the corresponding breathing state and the time between breathing, thereby obtaining the frequency of breathing and the judgment of whether apnea has occurred. Fourth, observation of whether the difference between the temperature value of a certain sampling point in the current array and the previous sampling point is not negative is required, and also whether the difference between a certain humidity value and the previous sampling point is positive. Fifth, if the conditions of step 4 are met, and the conditions of step 4 can be maintained for more than 1.5 s (because the human body expiration time is generally about 1.5 s), it proves that the current subject is breathing, and the time of breathing will increase as the sampling continues to increase. If the conditions in step 4 are no longer met, it means that the subject's breathing state has ended, and the ending time will continue to increase with the sampling point interval. When the ending time exceeds 15 s, it can be determined that apnea has occurred.

The algorithm can successfully extract the breathing cycle from the temperature and humidity change curve caused by the breathing airflow. The fluctuations in temperature and humidity of the breath airflow reflect the condition of human breathing to a certain extent, which has a certain degree of research significance. At the same time, the algorithm runs on a Bluetooth chip. The Bluetooth chip obtains data from the temperature and humidity sensors in real time, and the algorithm processes the information in real time. The

Bluetooth chip simultaneously passes the temperature, humidity, and breathing state data obtained by the algorithm through the operating system inside the Bluetooth chip program. After a series of hexadecimal conversion processes, the data are transmitted to the mobile application terminal by means of characteristic values notification, thereby achieving the goal of monitoring the subject's apnea during sleep with the smallest system volume [29]. An LED (Light Emitting Diode) screen display or buzzer alarm is not used, as neither is conducive to reducing the size of the wireless monitoring system.

2.2.3. Wearable Medical Sensors for Detecting Body Temperature

Body temperature is one of the important indicators that reflect the health of the human body. Accuracy of monitoring also directly affects the health of the human body. Knowing the specific value of the human body temperature can indirectly obtain the health information of the human body. This is of great significance to the prevention, infiltration and treatment of diseases, especially the prevention and control of influenza during the new coronavirus epidemic. Many scholars have conducted related research on body temperature detection with medical sensors (Table 3). Kumar et al. (2017) demonstrated ultra-fast detection and a reversible MoS_2 gas sensor at room temperature. By measuring body temperature, it was found that under light excitation, MoS_2 exhibits enhanced sensitivity, ultra-fast response time (29 s), and excellent recovery rate of NO_2 (100 ppm) at room temperature. This is a significant improvement in sensitivity, and the sensor has reliable selectivity to NO_2 and various other gases [30]. Liu et al. (2018) proposed and developed a resistive flexible NH_3 sensor, which was prepared by depositing polyaniline-cerium dioxide (PANI-CeO_2) nanocomposite film on a flexible polyimide (PI) substrate by an in situ self-assembly method. By comparing the morphology, structure and chemical characteristics of pure PANI and PANI-CeO_2 nanocomposites, and their effects on temperature detection, it was found that the PANI-CeO_2 thin-film sensor enhanced the response; shortened recovery time; produced a perfect response concentration linearity; had good reproducibility, excellent selectivity, remarkable long-term stability, ultra-low detection concentration (16 ppb) and theoretical detection limit (0.274 ppb); and had excellent flexibility, with no significant reduction in response after 500 bending/extension cycles [31]. By analyzing the tissue-like mechanical compliance and good biocompatibility of a self-healing hydrogel-bioelectronic device, Ge et al. (2019) proposed a self-healing, durable, heat-resistant and dual-sensing hydrogel sensor. They found that the hydrogel-bioelectronic device had superior mechanical and thermal sensitivity, and could realize a flexible touch keyboard for feature recognition and a "heat indicator" for human forehead temperature detection [32]. Huang et al. (2019) prepared a flexible hybrid film composed of graphene nanoplatelets (GNPs) and multi-walled carbon nanotubes (MWCNTs) for use as a multi-functional temperature and liquid leakage monitoring sensor, based on piezoresistive effect. The experimental results showed that with the increase in GNP content, the hardness and Young's modulus of the hybrid film decreased, but the thermal conductivity showed the opposite trend. The resistance of the hybrid film decreased linearly with the increase in temperature. As the amount of solvent adsorbed increased, the resistance change increased linearly. These characteristics prove the potential applications of hybrid membranes in detecting temperature and liquid leakage [33]. Wang et al. (2020) reported a multi-functional sensor composed of a hydrophobic membrane and graphene/polydimethylsiloxane sponge. It was found that in the case of temperature stimulation, the sensor displayed a temperature-sensing resolution of 1 Kelvin through the pyroelectric effect. The sensor could generate output voltage signals after physical contact with different flat materials, following the principle of contact induction charging, and the corresponding signals could be used to infer material properties in turn. Therefore, this multi-functional sensor performed well in terms of low cost and material recognition, and provided a design concept to meet the challenges of functional electronics [34].

Table 3. Summary of research on temperature detection by medical sensors by different scholars.

Scholar	Type of Sensors	Component of Sensors	Effects
Kumar et al. [30]	Gas sensor	MoS_2	Enhanced sensitivity, ultrafast response time (about 29 s), and excellent recovery of NO_2 (100 ppm) at room temperature.
Liu et al. [31]	Resistance sensors	Flexible ammonia (NH_3)	Perfect response concentration linearity, good reproducibility, excellent selectivity, significant long-term stability, ultra-low detection concentration (16 ppb) and theoretical detection limit (0.274 ppb) and excellent flexibility, no significant response after 500 bending/extension cycles.
Ge et al. [32]	Hydrogel sensor	Hydrogel	With superior mechanical feeling and thermal sensitivity, it can realize a flexible touch keyboard for feature recognition and a "heating indicator" for human forehead temperature detection.
Huang et al. [33]	Piezoresistive effect sensor	Graphene nanosheets and multi-walled carbon nanotubes	With the increase in GNP content, the hardness and Young's modulus of the hybrid films decreased, while the thermal conductivity showed the opposite trend. With the increase in solvent adsorption amount, the change of resistance increases linearly. It can be potentially applied to the detection of temperature and liquid leakage.
Wang et al. [34]	Thermoelectric effect sensor	Hydrophobic Films and Graphene/Polydimethylsiloxane	Excellent performance in low cost and material identification provides a design concept to meet the challenges of functional electronics.

In the review of the research by the above-mentioned scholars, it was found that detection of the basic physiological parameter of human body temperature does not only reflect the current health status of the human body, but is also a key element for maintaining physical health and normal physiological activities. Therefore, the use of wearable medical sensors is extremely important for human body temperature detection.

2.2.4. Wearable Medical Sensors for Detecting Blood Oxygen Saturation

The main route of transmission of oxygen in the blood is hemoglobin. Oxygen saturation is determined by oxygenated hemoglobin. First, oxygen enters the lungs when the human body breathes, and then enters the blood. The blood transports oxygen to the various organs of the human body, which is also the percentage of available hemoglobin that carries oxygen. The specific measurement of the content of oxygenated hemoglobin is found using the characteristics of oxygenated hemoglobin. Oxygenated hemoglobin and deoxygenated hemoglobin absorb light of different wavelengths in a specific way. The wavelength of light is very short: the unit of measurement is the nanometer, the wavelength of red light being around 650 nm, and the wavelength of infrared light being around 950 nm [35,36].

The measurement of blood oxygen saturation uses the characteristics of oxyhemoglobin and deoxyhemoglobin to absorb light of different wavelengths in a specific way. Oxyhemoglobin absorbs more infrared light than red light, and deoxyhemoglobin absorbs more red light than infrared light. Finally, the heart rate blood oxygen sensor analyzes the ratio of oxygenated hemoglobin and deoxyhemoglobin in the arterial blood that absorb two different wavelengths of light. The absorption ratio R of the two wavelengths of light is calculated, and then the blood oxygen saturation is calculated according to the standard model ($SpO_2 = HbO_2/(HbO_2 + Hb) \times 100\%$) for calculating SpO_2 [37].

In the process of blood oxygen saturation measurement, many scholars also put forward their own opinions (Table 4). Lee et al. (2018) believe that the pulse oximetry sensor, as a device for monitoring the basic human health, plays a key role, while also having a large consumption. Therefore, an ultra-low-power reflective patch pulse oximeter sensor was proposed, using the design freedom provided by organic technology. Through optical simulation of color-sensitive light propagation in human skin, the proposed monolithic integrated organic pulse oximeter sensor showed successful operation at an average electric power as low as 24 μW. Therefore, it was demonstrated that organic devices not only have the advantages of appearance in such applications, but also have great potential as supporters of all-day wearable health monitoring systems [38]. Khan et al. (2018) proposed a flexible printed sensor array composed of organic light-emitting diodes and organic photodiodes. The array sensors reflected light from tissue to determine blood oxygen saturation. It was finally verified that the sensor measured the blood oxygen saturation of the forehead with an average error of 1.1%, and created a two-dimensional oxygenation map of the adult forearm under the pressure cuff-induced ischemia. In addition, a mathematical model was proposed for the detection of blood oxygen saturation to determine oxygenation in the presence and absence of pulsating arterial blood signals. Therefore, the mechanical flexibility, oxygenation mapping capability, and the ability to place sensors in different positions of the reflective oximeter array proposed in this study make it promising for medical sensing applications, such as real-time chronic disease monitoring and tissue, organ, and postoperative recovery management of wounds [39]. Elgendi et al. (2019) used medical sensors generated by photoplethysmography (PPG) to detect blood oxygen saturation for outpatient care and general health monitoring. They found that this type of sensor device can collect pulse oximeter signals and can obtain accurate and continuous blood pressure measurements from mobile and wearable devices [40]. Janani et al. (2020) evaluated the diagnostic accuracy of dental pulse oximeters, thermal tests, and electric endodontic testers with custom sensor holders in assessing actual pulp status. They also assessed the oxygen saturation level of control healthy teeth, non-living teeth and irreversible pulpitis teeth. Finally, a randomized controlled trial found that the customized scaffold used in this study helped to provide an accurate response to the pulp vitality test. At the same time, under different pulp conditions, the diagnostic accuracy of the dental pulse oximeter was higher, followed by cold and hot pulp testers, with electric pulp testers having the lowest diagnostic accuracy [41]. Pereira et al. (2020) used sensors to record blood volume changes and used PPG to extract heart rate and other physiological parameters to inform users of activity, sleep, and health [42].

Table 4. Review of research on sleep monitoring by wearable medical sensor.

Scholars	Sleep Monitoring by Wearable Medical Sensors	Achievements
Nakamura et al. (2019) [43]	Wearable in ear electroencephalogram (ear EEG) was used for night sleep monitoring	It was feasible for in-ear sensor to monitor night sleep outside the sleep laboratory, which reduced the technical difficulty related to PSG.
Li et al. (2020) [44]	A system based on bed vibration sensor was proposed	Accurately monitored physiological parameters during sleep, such as HR, RR, body movement, and sleep posture.
Kim et al. (2020) [45]	A wearable multi-biological signal wireless interface for sleep analysis was designed	The correlation of four sleep stages was 74%.
Alfarraj et al. (2021) [46]	A non-synchronous sensor data analysis (USDA) model was introduced	Responsive healthcare solutions using asynchronous WS-data helped achieve greater efficiency and reduce the Complexity, when evaluating healthcare system performance.

2.2.5. Wearable Medical Sensors for Monitoring Sleep

Monitoring sleep aims to judge the quality of sleep and facilitate the detection of sleep diseases, such as common sleep apnea syndrome. In people's work and rest, sleep interruption may affect neural function, and may even be a symptom of physical and mental disorders. The miniaturization of wearable medical sensors and the progress of computing power have become favorable technologies for monitoring human physiological conditions in real-world scenes. Many scholars in related fields have studied their application in monitoring sleep (Table 4). Nakamura et al. (2019) proposed wearable in-ear electroencephalography (ear EEG) for night sleep monitoring as a 24/7 continuous and unobtrusive technology for community sleep-quality assessment. The results showed that the in-ear sensor was feasible for monitoring night sleep outside the sleep laboratory, but also reduced the technical difficulties related to PSG, and this technology was the key to affordable medical treatment and future electronic health [43]. Li et al. (2020) proposed a system based on a bed vibration sensor to monitor important parameters during sleep, including heart rate (HR) and respiratory rate (RR), body movement, and sleep posture. Finally, the short-term and long-term experiments on different participants and different beds indicated that the proposed system achieved satisfactory accuracy [44]. Kim et al. (2020) introduced a wearable multi-biological signal wireless interface for sleep analysis. It realized comfortable sleep monitoring through a direct sleep-stage classification function. Finally, they verified the system and found that its low-power headband analysis device was used for wearable sleep monitoring, in which the direct sleep-stage classification was performed based on the decision tree algorithm, with the correlation of the four sleep stages being 74% [45]. Alfarraj et al. (2021) introduced an unsynchronized sensor data analytics (USDA) model to effectively process wearable device data without considering time factors. They found that a responsive healthcare solution using asynchronous WS-data helped to achieve better efficiency and reduce complexity in evaluating healthcare system performance [46].

The review of the above scholars' research reveals that wearable devices are mostly used to monitor sleep parameters in different ways, such as brain map, HR, RR, etc., and to judge sleep quality by understanding the relevant parameters. Thus, wearable devices monitor physiological parameters such as respiration; the overall framework is shown in Figure 3. However, in the process of monitoring sleep, the security of data transmission and information was not particularly addressed.

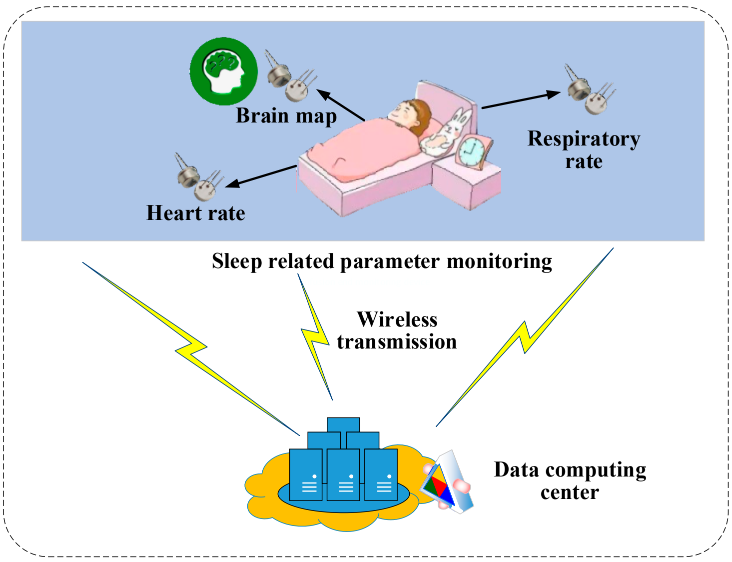

Figure 3. Framework of respiratory monitoring system of wearable medical sensors.

As shown in Figure 3, the respiratory monitoring system is mainly composed of N wearable sensor detection devices and data computing center. N wearable sensors are responsible for measuring the physiological parameters related to each sleep, and regularly sending the collected real-time parameters to the data computing center by using the wireless communication module. The data computing center is mainly responsible for processing the data received by the wireless module and using the LCD to display the processed physiological parameter information, thereby obtaining the sleep quality.

3. Intelligent Prospect of Wearable Medical Sensors

Because of its powerful data collection function, the sensor has more and more application fields. Among them, medical health is a necessary field for people's lives, and the role of sensors cannot be ignored. With the rapid development of technologies, such as the Internet of Things and artificial intelligence, medical sensors are also developing in the direction of intelligence. Medical sensors no longer appear as a single individual device, but in the form of a wearable medical sensor system.

3.1. Intelligent Prospect Method of Wearable Medical Sensors

With the rapid development of communication technology, 5G networks have basically achieved full coverage, and at the same time, the Internet of Things (IoT) technology has become more and more complete. However, in the era of the Internet of Everything, when wearable medical sensor systems can transmit and browse the collected data more intelligently, the security of wearable medical sensors has also become a future development trend [47].

With the ability of wearable medical sensors to collect more and more physiological parameter data from the human body, the performance of the wearable medical sensors themselves has also gained attention, such as more flexible sensor materials, high elasticity and high scalability [48,49]. With the emergence of new materials and new processes, these improvements in wearable medical sensors appear to be more feasible.

In addition, with the aging of society, the emergence of medical auxiliary equipment is also of great significance. It has also become a trend to combine wearable medical sensors with rehabilitation aids to develop a wearable medical sensor rehabilitation system that is consistent with the social elderly and movement-impaired groups.

3.2. Intelligent Prospective Applications of Wearable Medical Sensors

3.2.1. Prospects for Information Security of Wearable Medical Sensors

A wearable medical sensor system is mainly used to monitor human physiological parameters, which is a body sensor network (BSN). BSN technology, based on IoT, is one of the most important technologies in modern medical systems. It is a collection of low-power, lightweight wireless sensor nodes that are used to monitor human body functions and the surrounding environment [50]. Since human sensor network nodes are used to collect sensitive human information and may operate in harsh environments, strict security mechanisms are required to prevent malicious interaction with the system. Therefore, security research into human medical sensor networks has attracted many scholars' attention. Al-Turjman et al. (2018) found that in medical applications, the 5G-inspired Industrial Internet of Things (IIoT) paradigm enables users to interact with various types of sensors through a secure wireless medical sensor network (WMSN). However, the user's self-verification before each interaction is a lengthy and time-consuming process, which can interfere with residents' activities and reduce the overall performance of the medical system. In response to this problem, a context-sensitive seamless identity provisioning (CSIP) framework was proposed. The framework used a secure mutual authentication method of hash and global assertion value, which demonstrated that the mechanism could achieve the main security goal of WMSN in a short time [51]. Khattak et al. (2019) studied, in detail, the security issues relating to the perception layer of the Internet of Things, and described the key components of the Internet of Things (i.e., architecture, standards, and protocols) in the security environment of the perception layer, and then the security requirements of the Internet of Things. Second, after describing the hierarchical security of the general Internet of Things, two key enabling technologies of the perception layer, namely RFID and sensor networks, were discussed. Finally, open research issues and challenges related to the perception layer were identified and analyzed [52]. Anand et al. (2020) developed a double watermark, based on compression and then encryption, to protect the EPR (electronic patient records) data in the medical system, which produced some important characteristics. After using medical sensors to collect a large amount of medical data, experiments showed that the proposed method has the ability of intelligent medical treatment, and compared with the existing technology, the proposed work provides better performance in terms of robustness and safety [53]. Muzammal et al. (2020) introduced several trust models complying with the security requirements of IoT systems; they studied the security issues and requirements of IoT, the routing protocol for low power, and lossy network (RPL) routing protocols under various attacks, such as black holes, deception, hierarchy, etc. In addition, various mitigation methods and the meanings of the trust model in the Internet of Things to secure routing were analyzed. Finally, they measured trust in the IoT environment, including open issues and research challenges, and the meaning of trust as a security paradigm for IoT networks and routing protocols to gain a deeper understanding [54]. Zhu (2021) focused on the problem of energy imbalance in the infusion network, introduced the calculation method of network energy consumption under the direct transmission and minimum energy multi-hop routing protocol, and designed an improved network structure model to increase the communication scale. It was found that this method realized data aggregation and data transmission, and that the development of the monitoring system application platform adopted software technology. Furthermore, a cold chain transportation simulation experiment was carried out on the system, and the results showed that the hardware of the cold chain cooperative monitoring system was able to work normally, and the software design of the monitoring system met the basic requirements of the third-party logistics companies for the system; its accuracy also improved to a higher degree [55]. Singh et al. (2021) analyzed big data security, and other related technologies, using data collected by medical sensors in the field of health; they also analyzed their new trends in solving real-world application challenges. At the same time, various well-known cryptography, biometrics, watermarking and blockchain-based medical application security technologies were also investigated [56].

A review of the above-mentioned scholars' research found that there is a relatively large amount of research into the security issues of the Internet of Things system, but there is relatively little research into the safe interaction of user data in the medical field. Therefore, in today's globalized information networks, it is extremely important to protect people's medical information. The security of medical data is reflected in many aspects, such as data privacy, data integrity, data timeliness, data identity verification, data anonymity, and secure positioning [57–60]. Among them, data privacy is similar to that of wireless sensor networks and is regarded as the most important issue in BSN; data must be protected from leakage. If an attacker eavesdrops on communications and related key information, it may seriously harm the interests of patients, because the attacker can use the acquired data for many illegal purposes. Data integrity means that the system maintains the confidentiality of data and protects it from external modifications. If the attacker changes the data by adding some fragments, or processing the data packets, and forwards the changed data to the coordinator, a patient who may be critically life-threatened at that time could lose their life as a direct result, causing a great loss to society. In terms of the timeliness of data, if an attacker captures the data in transmission and uses an older key to replay it, so as to confuse the coordinator, it will cause irreparable damage to human health. Conversely, the secure location of the data can make it impossible for an attacker to report the wrong signal strength, thereby preventing them sending an incorrect report about the patient's location. Various security threats and attacks, such as data modification, counterfeiting, eavesdropping, and playback are thus avoided. Figure 4 presents the specific IoT security system for a wearable medical sensor network.

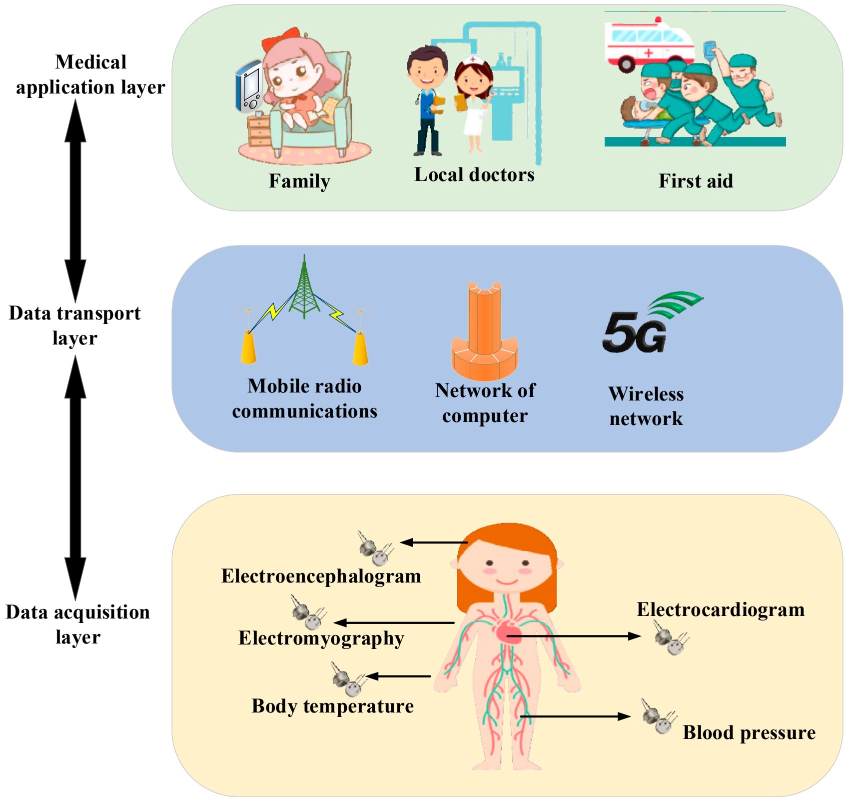

Figure 4. Framework diagram of IoT security system based on wearable medical sensor network.

As shown in Figure 4, in the IoT security system of the wearable medical sensor network, when the medical system server receives the data of a biosensor wearer from the local processor unit (LPU), it inputs the medical data into its database and analyzes it. Subsequently, depending on the degree of abnormality of the data, it is possible to interact with the wearer's family members, local physicians, and even the emergency department of a nearby medical center. When a person wears multiple biosensors on the body, and the medical system server receives regular updates from these sensors through the LPU, the server can maintain an operation table for each type of medical data received from the LPU. Consequently, the safety performance criteria of the wearable medical sensor system are achieved.

3.2.2. Prospects of Material Research for Wearable Medical Sensors

In the current medical field, most medical robots use an industrial robot as the operating platform, and it is difficult to achieve high levels of accuracy, replicability and reliability [61,62]. Nowadays, through mechanical structure, hardware design, and software optimization, medical robots have achieved, to a certain extent, the characteristics of flexible operation, and high levels of human-computer interaction and replicability for clinical operations. Generally, robots touch or intervene in human tissues during minimally invasive surgery. If the patient makes an involuntary movement, it is likely to affect the position and shape of the robot in the human tissue, so that the failure of the operation is likely to occur, and it is more likely to cause inevitable trauma to the subject [63]. Therefore, it is also extremely important to innovate materials, while improving the performance of medical intelligence. Many researchers have conducted investigations in this area. In view of the fact that real-time detection of low-concentration acetone vapor plays a decisive role in the early diagnosis of diabetes, Wang et al. (2018) fabricated a zoom medical sensor by using nanoscale porous crystal. They found that when the material was used as a wearable sensing material, it showed sensitivity and selectivity to acetone gas, which provided a basis for the manufacture of wearable medical sensors in the environmental and medical fields [64]. Zhou et al. (2019) analyzed a simple hydrothermal method for the synthesis and characterization of nanodisks. Morphological characterization confirmed the formation of clear nanodisks of high density and an average thickness of 60 microns. A wearable medical sensor was prepared, with a synthesized nanodisk as the electrode material. They found that the gas-sensing response, response time, and recovery time of the prepared wearable nanodisk gas sensor were 16.25 s, 52 s, and 41 s, respectively. The nanodisk was expected to be a candidate material for manufacturing wearable medical sensors for efficient toxic and harmful gas detection [65]. Yin et al. (2020) prepared a green conductive Ag nanowire (AgNW)/cellulose nanofiber (CNF) hybrid nanopaper by using surface solution mixing and vacuum filtration technology to prepare flexible sensors. Two different types of strain sensors were designed to study their application in strain sensing. They showed great potential in human motion and physiological signal detection. In addition, when mixed nanopaper was used as a wearable temperature sensor, it also showed stable and replicable negative temperature-sensing behavior, which provided guidance for the manufacture of flexible and biodegradable wearable sensors [66]. Punetha et al. (2020) analyzed three nanocomposite thick-film flexible gas sensors made of reduced graphene oxide (RGO), tin oxide (SnO_2), and polyvinylidene fluoride (PVDF). Chromium (Cr) was deposited on the surface of the device by an electron beam evaporation system to form the electrode of the device. The crystal structure, morphology, and electrical characteristics of the device were explored for the application of body temperature measurement. The results suggested that the sensor response was 49.2% and 71.4% sec, respectively, and the sec of 100 ppm and 1000 ppm hydrogen concentration were obtained, respectively. A novel low-cost flexible polymer-based nano wearable sensor was explored for the first time [67]. Cheng et al. (2021) synthesized a layered flower-like nickel-doped polymer using a one-step coprecipitation method and prepared a gas sensor, based on the prepared material, to evaluate its gas-sensing performance. The comparison revealed that the sensor showed excellent moisture resistance and long-term stability. Meantime, they proposed a simple solvent-dependent method to controllably synthesize nickel-doped sensing materials with excellent gas-sensing performance. When the materials were applied to wearable sensors, they showed a good application prospect in *n*-butanol detection [68]. Naresh et al. (2021) summarized the evolution of biosensors, the types of biosensors based on their receptors, transducers, and modern approaches employed in biosensors using nanomaterials, such as noble metal nanoparticles, metal oxide nanoparticles, nanowires, nanorods, carbon nanotubes, and quantum dots, and dendrimers and their recent advancement in biosensing technology with the expansion of nanotechnology [69]. Leonardi et al. (2021) focused on the main silicon-based biosensors, and discussed the most attractive sensor devices, starting with electronic sensors, silicon nanowire field-effect transistors, and porous silicon, as well as their optical substitutes, such as effective optical-thickness porous silicon, photonic crystals, luminescent silicon quantum dots, and finally, luminescent silicon nanowires. They principally investigated all these sensors in terms of working principle, sensitivity, and selectivity [70]. Leonardi et al. (2021) critically studied all the major metal-assisted chemical etching (MACE) routes of silicon nanowires in order to compare the advantages and disadvantages of different MACE methods. The authors studied all these manufacturing technologies from the aspects of equipment, cost, process complexity, and replicability. Moreover, they analyzed the possibility of commercializing these technologies for use in microelectronic technology, and investigated which technology was more suitable as an industrial method [71].

A review of the research of the above-mentioned scholars found that although the performance of wearable medical sensors improved after improvements in material preparation methods and diversity, wearable medical sensors alone cannot play a decisive role in the health of the human body. Therefore, small surgical robots with medical sensor systems have also become a discovery trend. A specific new-material medical-sensor-robot system model is shown in Figure 5.

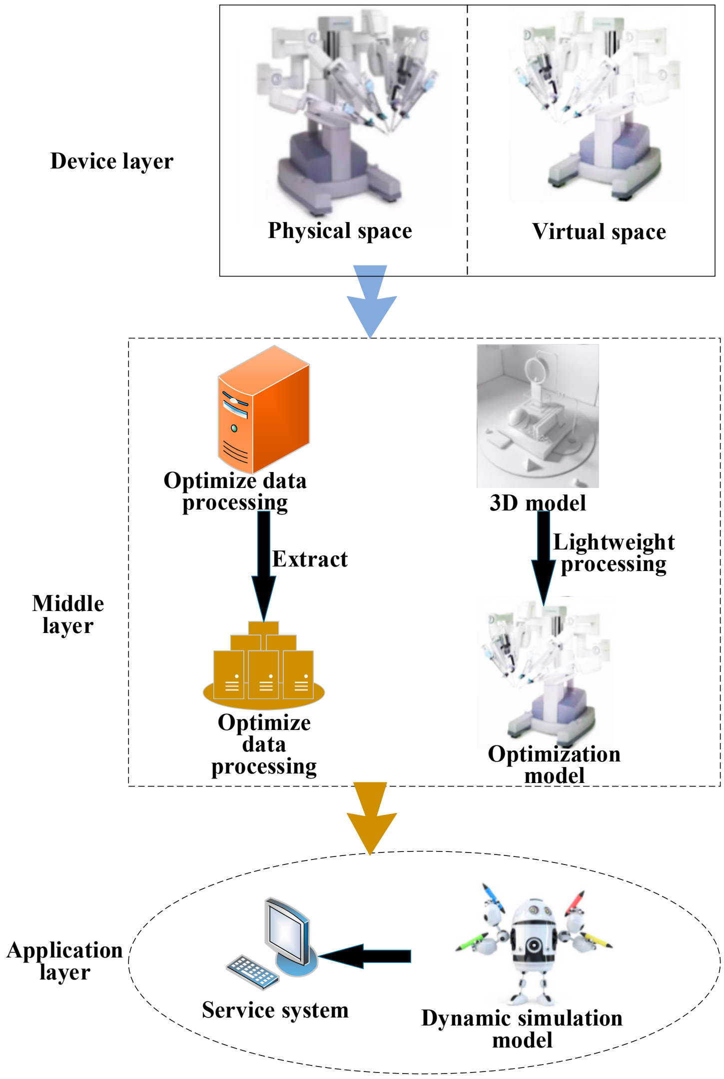

Figure 5. New-material medical-sensor-robot system model frame diagram.

As shown in Figure 5, the new-material medical-sensor-robot system collects human body data, taken as a physical object, via a four-axis medical robot. The OPC UA (OLE for Process Control unified architecture) communication protocol [72] was used to connect, process and transmit the data collected by the four-axis medical robot, and the script was used to drive the pre-drawn and optimized small medical robot model; thus, a dynamic simulation model was established. Data analysis performed on this model can provide services to medical staff and realize real-time status monitoring of the human health status of the medical sensor robot. At the same time, the bio-adaptability, biodegradability, neural interface control, high integration, miniaturization and other aspects of medical sensor robots will also become research hotspots in the future. A medical sensor robot system that is superior in performance, easy to manufacture, low in cost, and able to be mass produced is expected to appear in various fields of human production and life, truly serving mankind, and is a direction for future development.

3.2.3. Prospects of Intelligence-Assisted Rehabilitation of Wearable Medical Sensors

In addition, most traditional medical sensor rehabilitation devices are large in size, immobile, limited to a single training mode, and boring in terms of environment. The wearable lower-extremity exoskeleton rehabilitation robot is a cross-integrated discipline of mechanics, electronics, human-computer interaction, and bionics. It is worn on the patient's limbs, and by detecting the wearer's movement intention, it assists and protects the intelligent and mechanized rehabilitation equipment for rehabilitation training. Numerous research scholars in related fields have conducted research on medical sensor systems for rehabilitation assistance. Lv et al. (2016) used big data analysis technology to analyze the medical and health systems, and improved user experience through 3D stereo virtual reality glasses and immersive head-mounted displays, and at the same time used voice interactive games to provide patients with rehabilitation assistance [73]. Lv et al. (2017) designed, developed, repeatedly evaluated, and optimized an auxiliary training tool for the rehabilitation of dysphonia, based on actual clinical needs. This auxiliary tool can collect relevant data from patients through medical sensors, and at the same time play games and conduct voice training under the guidance of clinical therapists, without interference, or allow patients to independently perform rehabilitation training at home [74]. In order to be able to help people in the process of rehabilitation, Herrera-Luna et al. (2019) conducted research into current assistive technology combined with sensors that obtain biological signals from the body. They discovered sensor fusion for detecting hand movement, sensor fusion for exoskeleton control applications, and sensor fusion for serious games for hand rehabilitation. Moreover, through rehabilitation testing of the user's limb strength and the user's limb position, it was found that in hand rehabilitation exercises, flexion, extension, pronation, supination, strength grasping, radial/inversion, open hand, single-finger contraction, multi-finger contraction, pinching and holding hands and other movements can achieve the purpose of rehabilitation [75]. Nascimento et al. (2020) introduced the latest developments in sensors and systems for rehabilitation and health monitoring, and focused on the implementation of sensors and biomedical applications. This research found that a healthcare sensor can achieve family medical assistance and continuous health monitoring, and can be used as a body rehabilitation system and sensor, and auxiliary system [76]. Xiang et al. (2020) evaluated the safety and feasibility of a new type of rehabilitation robotic device for assisting patients with complete injury of lower limbs after spinal cord injury (SCI). Through randomized controlled trials with patients with spinal cord injury and complete motor paralysis, it was found that the use of a new robotic exoskeleton plan provided potential and meaningful improvements in the mobility of patients with SCI, and there were almost no adverse events [77]. Miao et al. (2021) combined the Internet of Things, machine learning, multi-modal sensors and smart system technologies to design a smart phone-based smart system to help stroke survivors improve upper limb rehabilitation. The experimental results showed that the proposed model can evaluate rehabilitation behavior, and the classification accuracy rates of very good, good and normal were 85.7%, 66.7% and 80%, respectively. At the same time, it can help stroke survivors carry out independent remote rehabilitation training, reducing medical expenses and psychological burden [78]. Mazzetta et al. (2019) proposed a wearable sensor system for automatic, continuous, and ubiquitous analysis of Freezing of Gait (FOG) in patients affected by Parkinson's disease. They found that the gyroscope and sEMG integrated in wearable devices could simultaneously sense the motion and action potential of antagonistic leg muscles [79].

A review of the research of the above-mentioned scholars found that due to the development of sensing technology, cheaper integrated circuits and connection technology, wearable devices and sensing devices used to monitor physical activity, whether for health, sports monitoring or medical rehabilitation, have been rapidly expanded. However, the construction of the actual medical sensor-assisted rehabilitation systems involves robotics, ergonomics, control theory, sensor technology, information-processing technology, and other disciplines, which require the integration of a variety of high-tech technologies [80,81]. Thus, the driving system, perception system, control system, man-machine matching system, man-machine interaction system and battery management system of any medical-sensor-assisted rehabilitation system are all extremely critical.

Therefore, while some breakthroughs and progress have been made for medical sensor-assisted rehabilitation systems, continuous improvement should include the modularization of the exoskeleton structure, the intelligentization of the control system, and the improvement of the performance evaluation of rehabilitation training effects. The theoretical research of modularization can be summarized as modular design of complex products, modular design of complex systems, and modular construction of industrial organization. The exoskeleton robot is divided into modules according to certain rules to make each module function independent and targeted, reduce the complexity of the exoskeleton robot, make breakthroughs in scientific research easier, and ultimately better meet the actual needs of different users [82]. In the intelligentization of control systems, the advent of the 5G era is promoting the in-depth development of artificial intelligence technology. The exoskeleton robot control system should keep pace with the times, so that the robot can learn independently, realize intelligent control, make operation simple and easy, enhance the user experience, and realize more comfortable and humanized rehabilitation training [83]. The improvement of the ability to evaluate the effects of rehabilitation training enables exoskeleton robots to successfully complete human-machine coordinated motion [84]. In the current rehabilitation training process, its power-assisted ability, power-assisted effect, bone stability, metabolic value, wearer fatigue, etc. cannot be monitored and presented. In the follow-up, real-time evaluation of the rehabilitation effect will be achieved by presenting the medical effect of each rehabilitation training. This will enable medical staff to formulate corresponding strategies in time, which will have a great effect on rehabilitation training.

3.2.4. Prospect of Intelligent Prediction Based on the Combination of Wearable Medical Sensors and Intelligent Algorithms

In recent years, the development of artificial intelligence and the research into artificial intelligence in the medical field have gradually begun, making people aware of the good prospects for the integration of artificial intelligence and medical care. Among them, the combination of the popular deep-learning field and sensor data-acquisition technology has shown relatively great application potential in disease prediction and drug response prediction [85]. Many researchers in related fields have conducted research into this combination. Mosenia et al. (2017) described the architecture of a typical system based on wearable medical sensors and discussed various research directions relating to wearable medical sensors, and how previous studies tried to solve the limitations of components used in wearable medical sensors system to meet the ideal design goal of an intelligent algorithm applied to wearable medical sensors [86]. Misra et al. (2020) proposed a scheme of dynamically selecting radio protocols in the energy-limited wearable Internet of Things medical system and considered using multiple radio protocols to send the physiological parameters sensed by patients to the server through local processing units (LPU). Through actual data and large-scale simulation, their results showed that compared with the existing schemes, the data rate increased by nearly 78% and the throughput increased by about 7% [87]. Qiao et al. (2021) proposed an intelligent feature-learning detection system (FLDS) based on deep learning combined with medical sensors for fetal congenital heart disease (CHD), a disease with a high mortality rate. A large number of their experiments showed that the accuracy of the proposed model algorithm could reach 91.9% [88]. Yu et al. (2021) also used deep learning combined with medical IoT technology to predict and analyze diseases. It was found that Internet-of-Medical-Things (IoMT) sensors can be used for spreading, which could ensure timely disease prediction and form a healthcare system with advantages in both prediction and time performance [89]. Li et al. (2021) proposed a multi-modal medical image fusion method with deep learning, based on the characteristics of multi-modal medical images and the actual needs of medical diagnosis. It was found that the system can realize batch processing of images, and at the same time showed its superiority in terms of visual quality and various quantitative evaluation standards [90].

A review of the research of the above-mentioned scholars found that the combination of medical sensors and deep learning technology can predict human health, such as fetal congenital heart disease. However, most of the medical sensor systems proposed by the above scholars were tested in the laboratory or under simulated conditions, and the relevant technical models were not applied to businesses. A series of tests are still needed before they can be used in the actual medical field. Meantime, some scholars have conducted predictive analyses on brain diseases in the medical field. For example, the use of fuzzy clustering and neural networks to predict brain tumors [91], and the combination of Digital Twins technology and artificial intelligence technology to predict diseases [92] are all intelligent developments in the medical field and are of great significance to improving human health to avoid disease.

4. Conclusions

Based on the collection of human physiological data in the medical field, the present work classifies and prospects the application and intelligent development of wearable sensors in the medical field. The application classification of wearable medical sensors shows that they play a very key role in detecting human physiological data, such as vascular infarction, respiratory intensity, body temperature, and blood oxygen concentration. The intelligent development of wearable medical sensors was prospected. The technologies for improving safety performance and integrating with assisted rehabilitation were explored to provide new development opportunities for the intelligent development of the medical field and real-time monitoring of human health. Meantime, analyzing and summarizing the research of scholars in the related fields of medical and artificial intelligence will help to improve the wearable medical sensor materials. Finally, such materials will realize the real-time detection of temperature, humidity, sensitivity, surface roughness, and other parameters, and afford high sensitivity and multi-functionality, together with a high level of flexibility, and self-healing, self-cleaning, a self-power supply, and transparency.

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