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Wearable Technology: Merging Computer Processing with Sensor Technology for Health Monitoring

Min Ren* and Ning Du

Department of Mathematics and Information Engineering, Liaocheng University Dongchang College, Liaocheng 252000, China

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We explored how to integrate advanced sensor technology and computer processing in wearable devices for healthcare in terms of applications, innovations, and challenges. The technology for wearable devices has rapidly evolved from simple fitness trackers to sophisticated medical devices. Wearable devices employ the real-time monitoring and personalized feedback of health-related signals. Through a literature review and case study, the effectiveness of managing chronic conditions and supporting telemedicine of wearable devices was assessed. The results showed that data accuracy, privacy, and accessibility are important in using wearable devices. At the same time, sensor data accuracy, robust data encryption protocols, and user interfaces are also critical in integrating sensor technology and computer processing. The integration of artificial intelligence and blockchain technologies is also required for wearable devices to provide proactive, personalized, and cost-effective solutions for healthcare.

1. Introduction

Wearable technology is a game-changer in healthcare as it has changed how people monitor and care for their health.(1) Fitness trackers, smartwatches, and medical wearable devices enabled users to access real-time health data. Wearable technology allows healthcare providers and patients to adopt a proactive, personalized, and data-driven approach to health management. Wearable technology is used to monitor daily activities and vital signs, and predict potential health risks for early warning and timely interventions. With the increasing prevalence of chronic diseases, preventive care is crucial, which necessitates the integration of wearable technology into healthcare. Hence, wearable technology has become inevitable in improving the quality of life and reducing healthcare costs.

In particular, health monitoring for the aging population becomes more important owing to their chronic conditions (diabetes, heart disease, and obesity) and the need for regular health monitoring.(2) Wearable devices enable the elderly to continuously monitor relevant health data and medical personnel to manage the elderly's chronic conditions efficiently for identifying and predicting anomalous patterns. Wearable technology enables lifestyle adjustments and

*Corresponding author: e-mail: renmin@lcudcc.edu.cn
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preventive care by ensuring effective health management.[3] Wearable devices in healthcare are expected to keep growing and improving owing to changes happening in the field, such as innovations in the technology of sensors, data analytics, and user interfaces.

Wearable devices are essential for individual health as well as societal benefits as they contribute to promoting public health and reducing costs associated with healthcare by encouraging a healthier lifestyle and an early detection of diseases.[4] The data collected from wearable devices are used to formulate healthcare policies and effectively utilize related resources. Wearable devices integrated into the healthcare system address pressing challenges such as the need for personalized preventive care by encouraging patients to manage their health autonomously.

In this study, we investigated how wearable technology, especially wearable devices, has integrated advanced sensor and computing technologies for healthcare. The advancement of wearable devices was reviewed in terms of their functionalities and algorithms to provide constructive and clear guidance principles for effective healthcare. The role of wearable devices in chronic disease management, preventive medicine, and telemedicine was also explored through various case studies and data analyses. The results were discussed to address the challenges in the development of wearable technology and devices, and the necessary specifications and guidelines for healthcare providers and patients.

2. Materials and Methods

2.1 Methodology

A literature review of specialized healthcare technology was conducted on academic articles, industry publications, and case studies. On PubMed, Scopus, and the Web of Science, keywords including "wearable technology", "health monitoring", and "sensor technology" were used to search relevant publications in the previous five years to understand current trends and practices in developing wearable devices. The searched literature was classified into subtopics, including the history of wearable technology, parts of wearable devices, their use in health monitoring, and the advancement and role of wearable devices in medicine.

Data were also gathered by interviewing healthcare and technology professionals who had experience in implementing wearable technology. Data, including the device's accuracy, user adoption degree, and clinical results, were collected to evaluate the effectiveness of wearable devices in health monitoring. Previous case studies were referred to depict wearable devices' functioning in managing chronic illnesses and their role in preventive care.

By analyzing the various demographic groups using wearable devices, the market trends were also analyzed in this study. While wearable devices are becoming popular, the elderly have difficulty using them owing to accessibility issues. Therefore, the utilization of wearable devices in telemedicine to remotely monitor patients' health status and reduce healthcare service costs was also explored. The results present the impact of wearable technology in healthcare and address challenges in using the technology.

2.2 Data analysis

The effectiveness of using wearable devices in health monitoring was assessed on the basis of related technology, user interaction, and clinical results. The role of sensors, AI, and machine learning (ML) in data computation and remote monitoring was also analyzed. In the case study, a quantitative analysis method was adopted. Interviews were conducted to assess user experiences and difficulties using wearable devices. With the combination of the results, the usefulness of wearable devices in achieving health results and providing healthcare services was evaluated. The levels of effectiveness of conventional non-instrumented and instrumented health monitoring were compared. The benefits of wearable devices in real-time data collection and feedback were also identified. On the basis of the results, how to optimize healthcare systems and improve the population's overall health using wearable technology were discussed.

3. Wearable Technology for Health Monitoring

3.1 History

The history of wearable technology dates back several hundred years. Wearable devices have evolved from simple mechanical devices to complex digital ones. One of the earliest wearable devices is eyeglasses, invented in 1286. Peter Henlein, a German inventor, created a small portable watch that could be worn as a necklace as a wearable device. By the late 1600s, wristwatches became popular among women as decorative bracelets. A pedometer was also invented, inspired by da Vinci's idea, to measure walking distance. These inventions present the basic forms of wearable devices to enhance daily life and measure physical metrics. In the late 1800s, wearable hearing aids were invented as a new advancement in the application of wearable technology in healthcare. In the 20th century, progress was made in wearable technology, stemming from the miniaturization of electronic devices.[5] In 1904, aviator Alberto Santos-Dumont created a wristwatch for practical use while flying. In the 1970s, a calculator watch, a basic form of wearable technology, was created with a basic computing function. Sony® revolutionized the entertainment industry by creating a portable music device, the Walkman, in 1979. The first wearable computer appeared in the early 1980s, designed by Steve Mann. It was a backpack-mounted system that controlled cameras and flashbulbs. These developments demonstrated the growing interest in wearable devices that were seamlessly blended into daily life with usefulness.

The Samsung Galaxy Gear smartwatch, released in 2013, represented a milestone in adopting sensor technology for health monitoring with heart rate measurement and physical activity tracking.[6] In 2015, Apple launched the Apple Watch, which provided fitness tracking and communication in a complete app ecosystem. Smart glasses with augmented reality (AR) functionality, such as Google Glass, also presented advancements in wearable technology with built-in AI for health monitoring.

3.2 Components of wearable devices

3.2.1 Sensors

Wearable devices have multiple sensors, such as accelerometers, gyroscopes, and magnetometers for motion tracking, and optical sensors to measure heart rates and oxygen saturation. Sophisticated sensors for measuring electrocardiographs (ECGs) and electroencephalographs (EEGs) are also employed in wearable devices to monitor health conditions.(7) These sensors convert various sensed signals into digital ones to analyze users' health status using microprocessors (Fig. 1). For example, accelerometers sense the changes in velocity and orientation by employing piezoelectric crystals that produce voltage with mechanical stress applied.(8) Optical sensors with LEDs and photodiodes are used to detect changes in blood flow. The Beer–Lambert law (1) is widely used in optical sensors to measure oxygen saturation in the blood.

$$A = \log\left(\frac{I_0}{I}\right) = \varepsilon \cdot c \cdot l \tag{1}$$

Here, A is the absorbance, I_0 is the incident light intensity, I is the transmitted light intensity, ε is the molar attenuation coefficient, c is the concentration of the absorbing species, and l is the path length.

3.2.2 Computer processing

A computer processor is used for data acquisition, analysis, and storage. ARM Cortex-M processors are commonly used in wearable devices owing to their low power consumption and compact design (Fig. 2).(9) Algorithms are run by computer processors to analyze sensor data and produce results for users to observe. The ML models embedded in wearable devices to predict

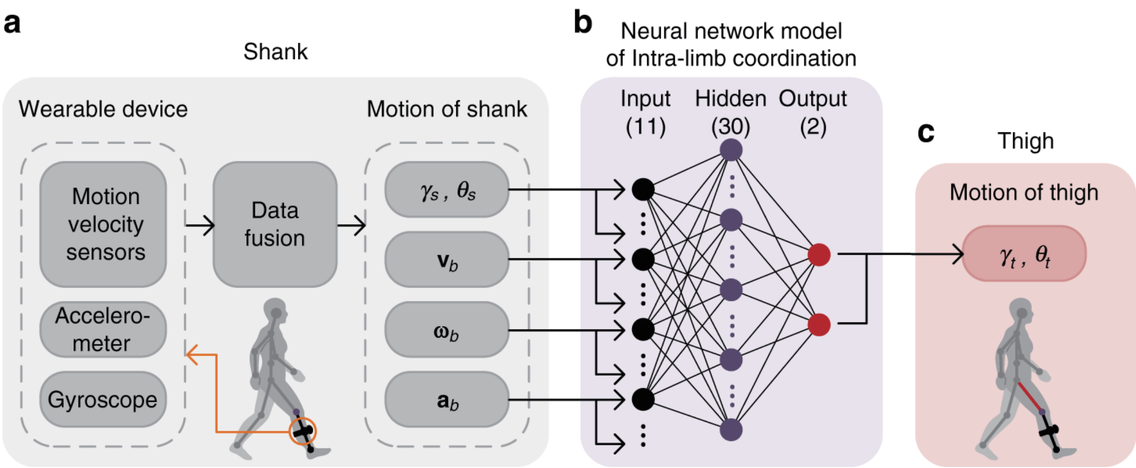

Fig. 1. (Color online) Sensing data and its process in wearable technology.(8)

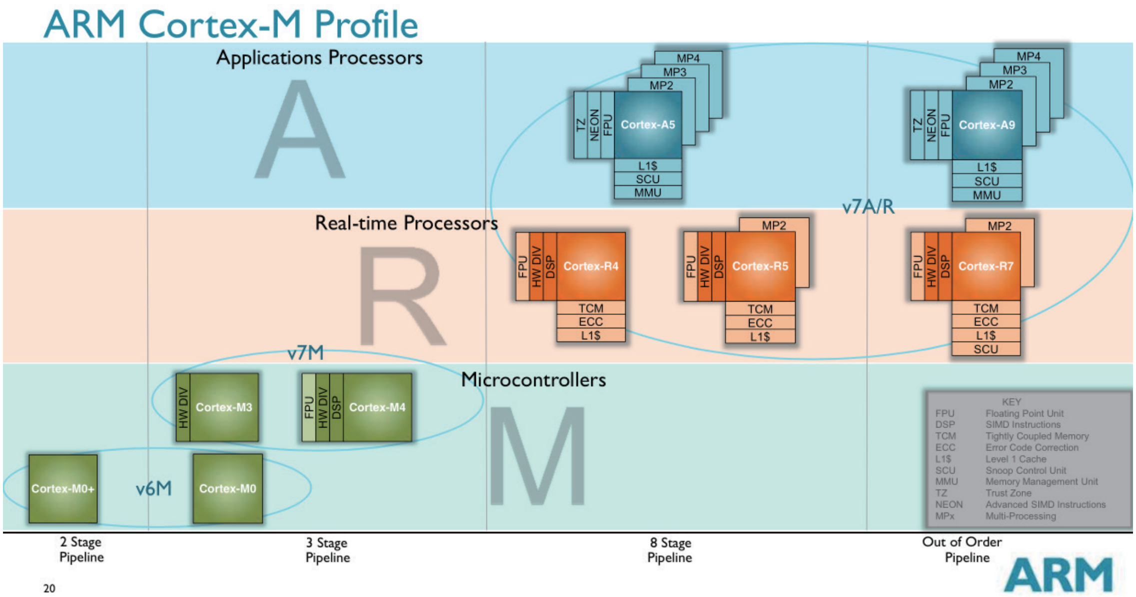

Fig. 2. (Color online) ARM Cortex-M processors used in wearable devices.

health risks based on heart rate anomalies or sleep cycles are also run by a computer processor. A memory module in a wearable device is also controlled by a computer processor to transmit data to a cloud server. AI run by a computer processor enhances wearable devices' processing abilities. For example, AI-powered hearing aids filter the background noise while amplifying the necessary sound based on real-time acoustic analysis. Simple logistic regression is usually applied for binary classification in ML using Eq. (2) in a computer processor.

$$P(Y=1)=\frac{1}{1+e^{-(B_0+B_1X_1+\dots B_nX_n)}} \tag{2}$$

Here, $P(Y = 1)$ is the probability of the positive class, B is a model parameter, and X is an input feature.

3.2.3 Connectivity

Wearable devices need to interface with other systems to analyze the data collected. Therefore, their connectivity is critical in wearable technology. Protocols such as Bluetooth Low Energy (BLE), wireless fidelity (Wi-Fi), or near-field communication (NFC) are widely used owing to their ease of use and compatibility with cloud databases. BLE is preferred owing to its low power consumption and fast data transmission in short distances.[10] NFC facilitates fast data transfer over a distance of 20 cm and is widely used for contactless payments or authentication. IoT protocols are used with such technologies for remote monitoring and control via the Internet. For instance, medical wearable devices transmit patient information to healthcare practitioners for timely analysis and intervention to reduce the risk of complications. Easy access to data and information increases the usefulness of wearable devices in telemedicine (Fig. 3).[11]

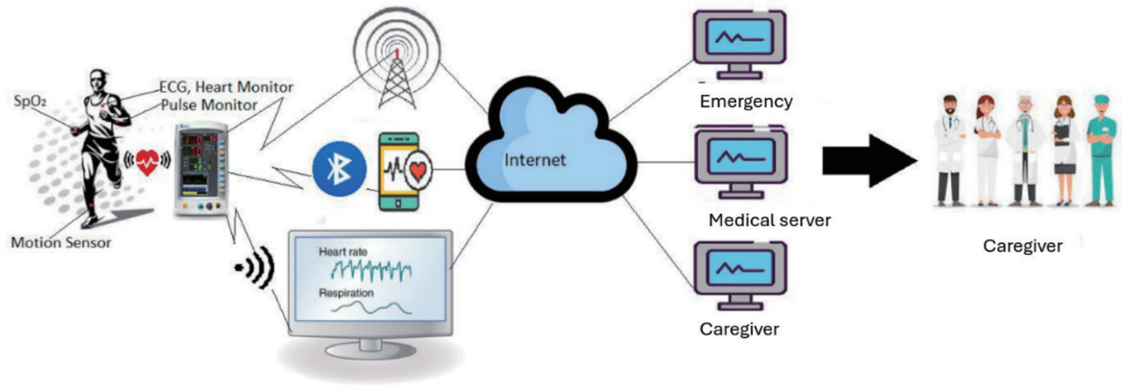

Fig. 3. (Color online) Wearable devices connected to various systems.

To assess the quality of Bluetooth communications, the received signal strength (*RSSI*) is calculated as

$$RSSI = 10_n \log_{10}(d) + A, \quad (3)$$

where n is the signal propagation exponent, d is the distance from the transmitter, and A is the received signal strength in 1 m.

3.2.4 Power supply

Wearable devices adopt rechargeable lithium-ion or lithium-polymer batteries because they are small but have high energy density. For low-power sensors such as fitness trackers, lithium coin cell batteries are used because they are small but have extended operation time. Wearable devices need efficient power management circuits to save energy during operation. These circuits manage the voltage level and power consumption by turning off inactive components and supplying power to active components. Several wearable devices are self-powered with solar panels or kinetic energy harvesters (Fig. 4).(12)

3.2.5 Materials

Wearable devices require lightweight, flexible, and durable materials to ensure comfort and user experience. Silver and stainless steel are commonly used as casing materials.(13) Medical wearable devices are made of silicone elastomers to avoid skin irritation. Usually, easily bent and washable materials are used in wearable devices. In general, advanced materials are used in ultrathin wearable devices. Figure 5 shows the main components included in wearable devices.

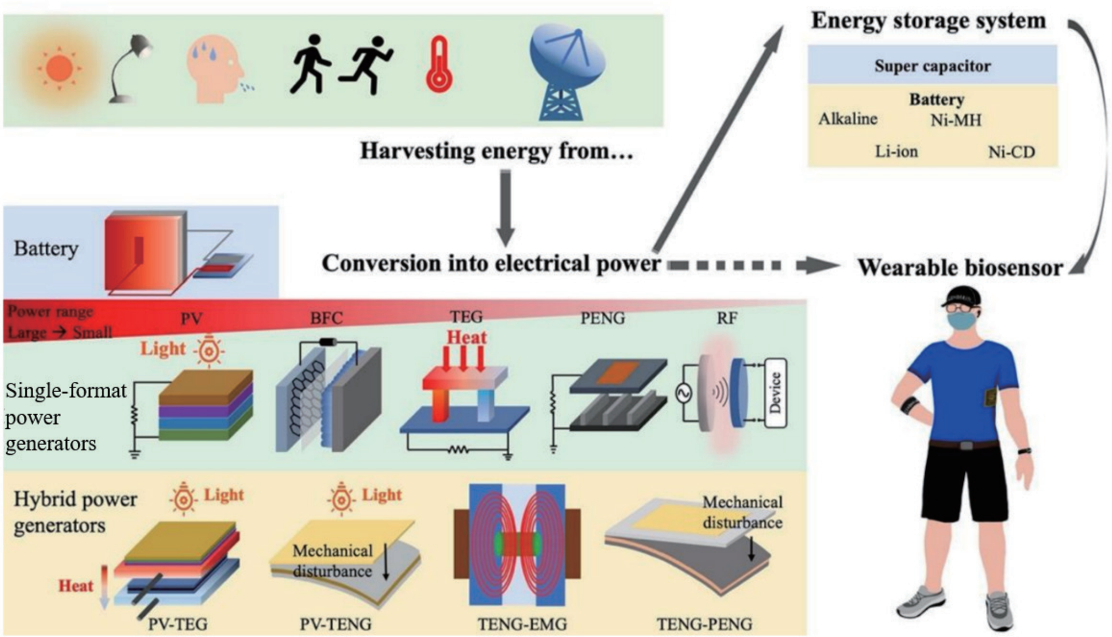

Fig. 4. (Color online) Power sources for wearable devices.[12]

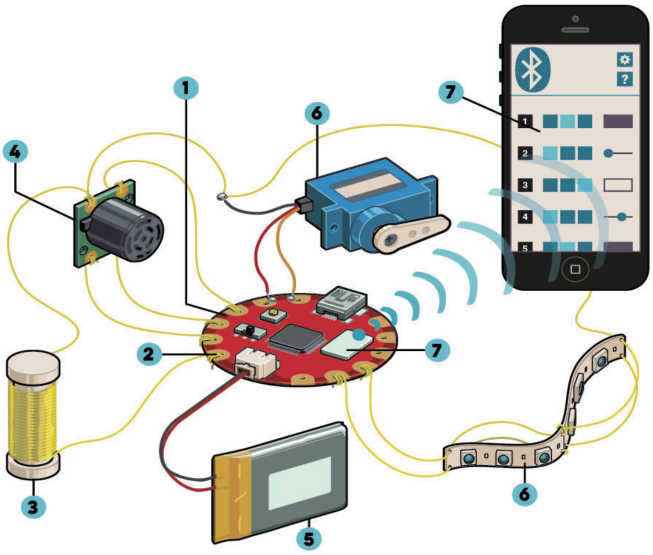

Fig. 5. (Color online) Components of wearable devices: (1) control, (2) input/output, (3) conductive textiles, (4) sensors, (5) power supply, (6) actuators, and (7) networking module.

3.3 Wearable devices in health monitoring

Wearable devices used for health monitoring are grouped into several categories depending on their purposes. Fitness trackers are commonly used to monitor physical activities, heart rates, and sleep patterns. Fitbit Charge 4 and Garmin vívosmart 4 are common fitness trackers and are connected to smart devices. Smartwatches are also widely used as they integrate traditional timepieces with sophisticated health-monitoring sensors. Apple Watch Series 6 and Samsung Galaxy Watch 3 are popular smartwatches mainly used to monitor ECG, blood oxygen level, and stress degree. They are popular with fitness enthusiasts as well as patients.(14) Medical wearable devices emphasize their capability to monitor the chronic conditions of patients for clinical procedures. Continuous glucose monitoring (CGM) is adopted in wearable devices to monitor accurate blood sugar levels for diabetic patients. AliveCor KardiaMobile is widely used for ECG monitoring. Medical wearable devices are required to obtain regulatory approval (Fig. 6).

Wearable devices are widely used for personal health monitoring, chronic disease management, preventive healthcare, telemedicine, and elderly care. With the advent of wearable technology, personal health monitoring has become vital for daily activities.(15) Fitness trackers and smartwatches provide information on steps taken, calories burned, heart rates, and sleep quality, which are used to improve personal lifestyle. Smartphone applications provide tailored recommendations based on fitness trackers for effective health management. Wearable devices are also used in medicine. They are used to diagnose arrhythmia for timely intervention and monitor CGM to alert diabetic patients. Wearable devices are used to monitor ECG and blood pressure (systolic and diastolic pressures) for remote monitoring and telemedicine. With the devices, patients can have timely assistance and medical treatment for an effective prognosis. Therefore, preventive healthcare is enabled by using wearable devices. Clinical parameters such as oxygen saturation level and body temperature can be measured and monitored using biosensors. The data are used for the diagnosis of various diseases.(16) With AI analytics, the monitored data are analyzed to prevent health risks. Such preventive health care is essential for sustaining the patient's health (Fig. 7).

In telemedicine, wearable devices are used with cloud platforms for clinicians to perform real-time analyses. Patients living in remote areas or the elderly benefit from telemedicine and wearable devices.(7) In particular, wearable devices assist the healthcare providers of the elderly

Fig. 6. (Color online) Various wearable devices.

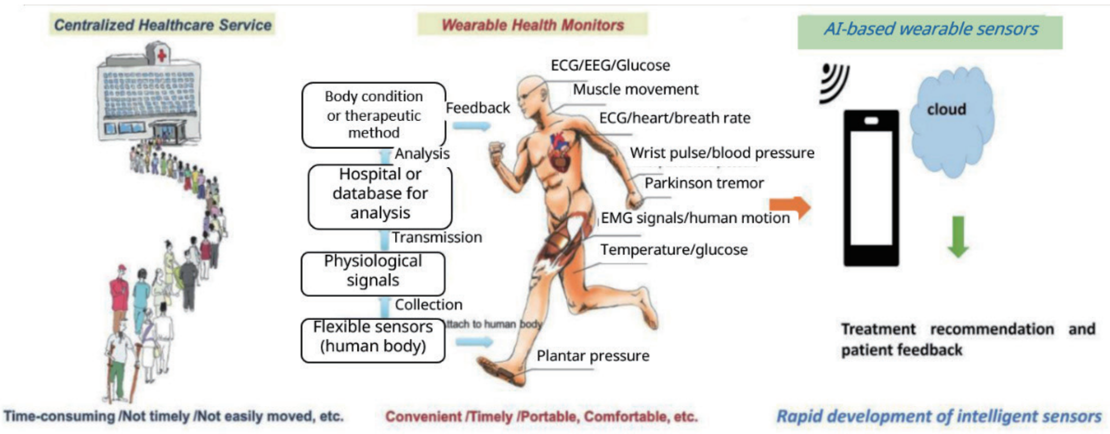

Fig. 7. (Color online) Health monitoring and healthcare services using AI analytics and wearable devices.

in monitoring and sensing data. The elderly's falls are also detected and alert the caregivers to emergency services. GPS-enabled wearable devices also help track the location of the elderly with cognitive impairments. These functions of wearable devices allow the elderly and patients living in remote areas to have appropriate medical services and maintain their health (Fig. 8).

4. Advanced Technology in Wearable Devices

4.1 Sensor technology

Advanced sensors enable wearable devices to perform sophisticated health monitoring with accuracy. Wearable devices integrate various sensors such as optical sensors to monitor heart rate and oxygen saturation level, accelerometers to monitor posture and body balance, and gyroscopic sensors and dermal infrared sensors to monitor skin temperature and blood flow. Noninvasive glucose and PPG-based blood pressure monitoring is also conducted with corresponding sensors. The monitored data are used to effectively manage the chronic diseases of patients as well as to monitor the health status of ordinary users. Recently, the Novosound Slanj platform with ultrasound sensors has been used to monitor arterial wall movement, enabling cuffless and wireless blood pressure monitoring. Recently, smart rings have been used for sleep quality monitoring, stress analysis, smart home integration, and other functions. The Viv Ring adopts temperature and optical sensors to monitor biometric signals such as heart rate variability and provide a generative sleep aid (Fig. 9).

Such advanced sensors ensure accurate diagnoses, personalized medicine, and preventive medical care, and enhance the capability of wearable devices for effective health management, being essential devices in daily life.

4.2 AI and machine learning integration

AI and ML enable real-time data analysis and enhance the capabilities of wearable devices. AI algorithms analyze the sensor data collected from wearable devices and detect patterns that

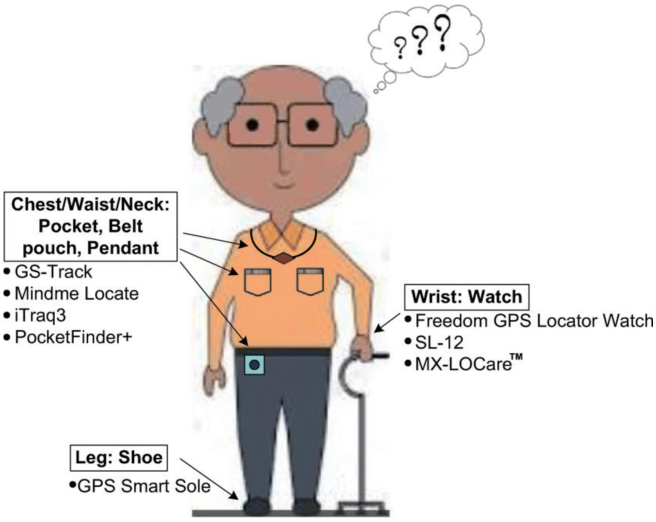

Fig. 8. (Color online) Wearable devices for medical care for elderly.

(a) (b)

Fig. 9. (Color online) (a) Novosound Slanj platform and (b) Circular Ring 2.

signal potential health problems. For instance, AI-embedded wearable devices identify arrhythmias and predict glucose level changes, enabling timely medical action. By using ML, the accuracy of prediction is enhanced and the noise in sensor data is removed. Hierarchical Long Short-Term Memory is mainly used in medical applications of ML.[7] AI is widely used in automated personal healthcare. AI-embedded wearable devices enhance lifestyle by monitoring user habits and processing data to provide personalized care. The devices are used in sports training as performance metrics, and recovery times are offered to avoid injuries. The devices are also used in telemedicine.[17] Innovative wearable devices with AI and ML highlight the effectiveness of the health management system (Fig. 10).

4.3 Advanced materials

Flexible and biocompatible materials are used to enhance the user comfort and device durability of wearable devices. The continuous wear of the devices requires flexible and

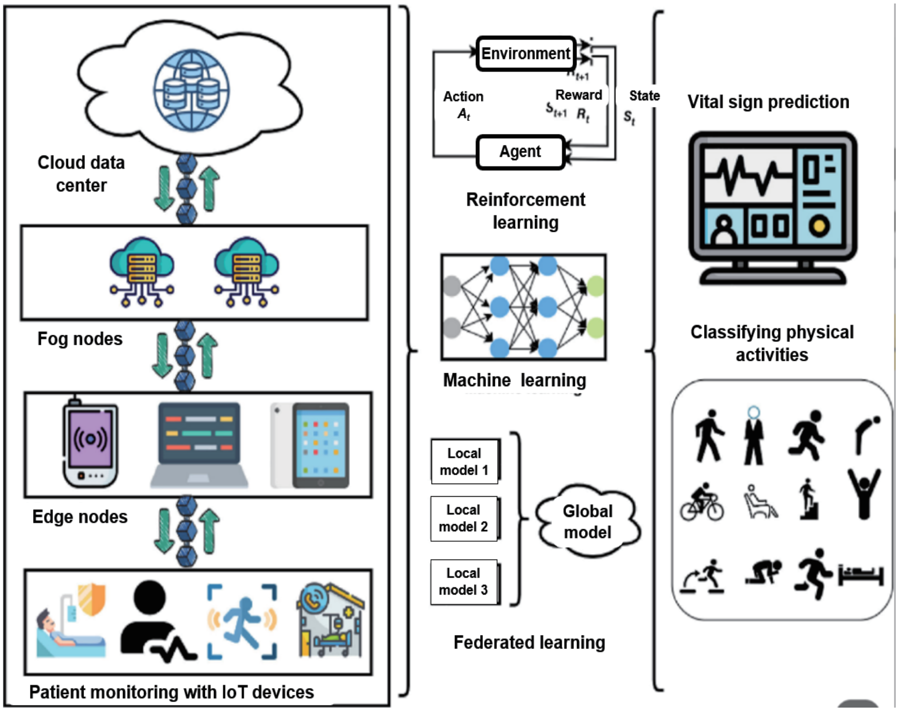

Fig. 10. (Color online) AI-enabled health management system.[17]

biocompatible materials to prevent discomfort or durability. Bioelectrodes made of single-wall carbon nanotubes (SWCNTs) grown on stretchable polystyrene-b-butadiene-b-styrene nanosheets have been introduced recently.[18] The bioelectrodes exhibit tremendous stretchability and are humidity-permeable, which prevents the accumulation of sweat. Such materials allow for accurate biosignal capture since they maintain mechanical stability under dynamic conditions and are a snug fit to the skin. The materials are used for long-term ECG or EEG monitoring devices. Epidermal electronics promote the development of ultrathin noninvasive devices without irritating and impeding movement. Advanced materials are being adopted more in next-generation wearable devices.

4.4 Future trends in wearable technology

In the future, AR and head-mounted displays are expected to be integrated into wearable devices. They have already been used in smart glasses and virtual reality systems. Such devices can be used in telemedicine by showcasing patient data for effective consultation. Blockchain technology is also applied to secure sensor data and protect privacy with integrity.[19] With these technologies, wearable devices can be developed to be an essential element of multi-sensor fusion systems with physical, chemical, and biological sensors. Such advancement enables monitoring hydration levels, electrolyte balance, and metabolic rates for more effective health monitoring.[19] Advanced energy harvesting (EH) technologies also enhance the operation of wearable devices, especially for long-term use.

4.5. Limitations of ambient EH for wearable devices

While ambient EH technologies (kinetic, thermal, or solar) are vital for battery-free wearable devices, their application is limited by the following engineering bottlenecks:[20)]

- Low power output density: Energy harvested from the environment is insufficient to consistently power active circuits and continuous wireless transmission.[20] Wearable EH devices rarely use power that exceeds 5 mW per square centimeter (mW/cm²) of areal power, while many system-on-chips require instantaneous power between 20 and 100 mW for active operation.[20]
- Intermittency and variability of supply: The energy source is highly dynamic and unpredictable.[21] Photovoltaic efficiency drops considerably under indoor or low-light conditions. Kinetic harvesters (piezoelectric or electromagnetic) rely on consistent, high-frequency body movement (e.g., fast walking), making them unreliable during sedentary periods or sleep.[20,21] Thermal energy harvesting is adopted but limited by the small temperature differential between the human body and the ambient environment, yielding a very low electrical output.[21]
- Integration, durability, and efficiency: By integrating EH components into small, flexible wearable devices, appropriate form factors can be obtained.[20] Flexible substrates and materials, essential for user comfort, reduce energy conversion efficiency.[21] Moreover, the lack of standardized, high-performance, and flexible energy storage (microbatteries or supercapacitors) to effectively manage the irregular input from EH systems must be addressed for practical viability.[20]

5. Case Study and Data Analysis

5.1 Case studies

5.1.1 Glucose monitoring for diabetic patients

The Freestyle Libre of Abbott Diabetes Care® with implantable chemical sensors monitors the blood glucose levels of diabetic patients. It can be worn on the back of the upper arm with an invasive sensor to determine blood glucose levels in the interstitial fluid between cells. The device provides increased discretion and ease of use, being adaptable to various patients' lifestyles. However, the device does not provide chronological data, which hinders healthcare providers from making appropriate long-term diabetes management plans. Patients cannot see the previous trends of their blood glucose levels owing to a lack of constant monitoring.

While minimally invasive CGM devices are widely adopted, the development of truly noninvasive CGM (NICGM) for integrated wearable devices, such as smartwatches, is hindered by technical and physiological barriers, preventing their widespread use in practical medical settings.[22] The challenge remains in achieving the necessary accuracy and reliability to make clinical decisions.[21,22] Current NICGM relies on optical (e.g., near-infrared or Raman spectroscopy) or radiofrequency methods, but suffers from the following issues:

- Signal attenuation and specificity: Biological tissues, especially the skin, contain a high concentration of water, which is a strong light absorber.[23] The concentration of glucose in the interstitial fluid (ISF) is significantly lower than that in water and other biological components (only 1 to 10% of the blood glucose density).[23] This disparity makes the glucose-specific signal extremely weak, resulting in a low signal-to-noise ratio that cannot yet be reliably managed by miniaturized wearable optics.[20,23]

- Physiological noise and variability: Measurements are affected by physiological noise and external factors, including motion artifacts, local skin temperature, and changes in hydration or blood perfusion.[23] Furthermore, the heterogeneity of tissue structure across individuals and measurement sites necessitates frequent, personalized calibration, which severely reduces the practicality and usability required for continuous, uncalibrated home monitoring.[22,23]
- Time lag: Even if accurate, noninvasive methods measure glucose in ISF, which exhibits a physiological delay (typically 10–20 min) compared with actual blood glucose levels.[21] This inherent lag compromises the ability of NICGM devices to provide timely alerts during rapid glucose fluctuations.[21]

5.1.2 Ring sensor for oxygen saturation level and heart rate monitoring

Blood oxygen saturation level and heart rate can be monitored using a ring sensor. This self-contained wearable device increases measurement accuracy through motion artifact reduction.[24] The design of the ring sensor is appropriate for the everyday monitoring of vital signs and the detection of hypertension and congestive heart failure. Although the ring sensor enables the determination of accurate cardiovascular parameters, motion artifacts affect its measurement reliability. However, the ring sensor is regarded as an efficient monitoring and management tool for patients and healthcare providers with chronic cardiovascular health conditions.

5.1.3 Wearable closed-loop drug infusion system

An innovative wearable closed-loop drug infusion system is used to administer insulin automatically depending on monitored blood glucose levels. An advanced insulin pump with a silicon sensor is used in the system for continuous glucose monitoring using microperfusion techniques. The system has a built-in Bluetooth module, allowing data collection, recording, and transmission to a personal digital assistant. The system automates real-time insulin administration and glucose level monitoring, and releases the burden of glucose measurement and insulin injection from the patients.[25] The system enhances the effectiveness of diabetes management by delivering an accurate and responsive insulin therapy.

5.2 Data analysis

The data measured by wearable sensors were compiled from 179 research articles with 10835733 participants.[11] Key findings are summarized as follows.

Table 1 shows the prevalence of smartwatches and fitness trackers in measuring the number of steps, heart rate, and sleep duration. Wearable devices for measuring specifically blood pressure and respiratory rate are widely used but limited in clinical use.

Table 1
Health parameters measured by wearable devices.

Health parameters	Number of related studies (%)	Device
Number of steps taken	95 (53.1%)	Fitness trackers
Heart rate	55 (30.7%)	Smartwatches, chest straps
Sleep duration	51 (28.5%)	Wristbands, smart rings
Blood pressure	3 (1.7%)	Specialized medical wearable devices
Skin temperature	3 (1.7%)	Biosensor patches
Respiratory rate	2 (1.1%)	Chest-worn devices

Wearable device types and their usage are summarized in Table 2. Fitness trackers are most used with a lower participant usage rate than other wearable devices integrated with data analytics platforms.(11) This underscores the scalability and widespread adoption of the platforms that analyzed data from multiple wearable devices for advanced health monitoring.

Traditional health monitoring methods largely depend on manual self-reporting and regular clinic visits, leading to a lack of data accumulation and medical professionals. Users do not have feedback in real time, which is a disadvantage for them in managing their health effectively. The traditional methods need the diagnosis of medical professionals, which requires time and costs.

Wearable devices with advanced technologies effectively monitor health parameters and physical activities. ECG sensors for heart rhythm detection and accelerometers for motion tracking also show high precision and accuracy. Real-time feedback through related applications enables users to take immediate action for any anomalies. The seamless integration of wearable devices into telemedicine and cloud-based systems enables healthcare providers to remotely access patients. Wearable devices are transforming healthcare systems and management, and their cost-effectiveness and capability enable users to actively manage their health. The comparison results in this study present enhanced accessibility, efficiency, and empowerment to the user of wearable devices.

5.3 Challenges

Despite its rapid progress, the widespread and clinical adoption of wearable technology is constrained by challenges, including data integrity, ethics, and fundamental hardware limitations. The continuous collection of highly sensitive physiological data necessitates the use of robust encryption protocols and decentralized storage solutions, such as blockchain integration, to maintain user trust and comply with stringent health regulations. While physiological sensor technology is mature, clinical-grade accuracy and specificity in complex noninvasive measurements must be ensured (Table 3). For example, in using NICGM, an acceptable signal-to-noise ratio must be achieved, and physiological confounding factors (e.g., water absorption) and the inherent low concentration of target analytes must be addressed.(23) Furthermore, the physiological time lag of interstitial fluid measurements must be minimized to provide timely alerts during acute glucose fluctuations.(21,22)

To meet the demand for smaller, flexible, and comfortable wearable form factors, reliable, long-lasting power is required. Current ambient EH solutions, including kinetic, thermal, and solar methods, still suffer from low power output density and supply intermittency, making them

Table 2.
Types of wearable devices and their usage.[11]

Wearable device type	Number of studies (%)	Number of participants (%)
Fitness tracker	86 (45.5%)	22823 (0.2%)
Accelerometer (worn on wrist, torso, and hip)	49 (25.93%)	299251 (2.66%)
Electrocardiogram chest patch or strap	21 (11.11%)	530332 (4.72%)
Smartwatch	12 (6.35%)	1259605 (11.2%)
Diverse wearable devices with data analysis platform	11 (5.82%)	9122758 (81.13%)
Distinct vital sign trackers (e.g., oximetry ring, temperature wristband tracker, blood pressure armband)	10 (5.29%)	10103 (0.09%)

Table 3
Comparison of traditional and wearable-device-using methods.

Feature	Traditional health monitoring	Wearable device
Data collection	Manual (e.g., clinical visits, self-reporting)	Automated (e.g., sensors collect real-time data continuously)
Frequency of monitoring	Intermittent (e.g., periodic check-ups)	Continuous (24/7 monitoring of vital signs and activities)
Accuracy and precision	Dependent on user or clinician accuracy	High precision with advanced sensors (e.g., ECG, PPG, accelerometers)
Feedback mechanism	Delayed (results after clinical analysis)	Real-time feedback via apps or alerts
Accessibility	Limited to healthcare facilities	Accessible anywhere with mobile connectivity
Integration with healthcare	Requires manual data sharing	Seamless integration with cloud platforms and telemedicine systems
Cost	High for routine clinical tests	Cost-effective for long-term use
User engagement	Minimal (passive role in health management)	High (active participation with personalized goals and insights)

insufficient to consistently power active computational components and continuous wireless transmission.[21,22] The lack of standardized, flexible, and high-capacity energy storage to manage the irregular power input from EH sources is also a barrier to be removed for battery-free wearable devices.[20] Finally, integrating AI requires the development of robust models that are trained on highly diverse, multi-modal datasets to ensure generalizability across different patient populations, while simultaneously maintaining explainability for clinical decision-making.

6. Conclusions

We explored the seamless integration of advanced sensor technology and computer processing in wearable devices, demonstrating their effectiveness in real-time health monitoring, chronic condition management, and supporting telemedicine. Through a review and case study analysis, we highlighted the important role of robust data encryption, enhanced sensor accuracy, and intuitive user interfaces in the successful merging of related technologies. The adoption of AI and blockchain is projected to enable more proactive, personalized, and cost-effective healthcare solutions. However, the transition of wearable technology from consumer-grade health tracking to clinically practical, autonomous medical devices is hindered by technological limitations that require more research efforts.

The technical barriers referred to in this study must be overcome to utilize the technology's full potential. First, significant hardware and algorithmic innovations are required to overcome the physiological constraints and signal interference that undermine the adoption of noninvasive sensing techniques. This is crucial in continuous blood glucose monitoring, where the current inability to accurately and consistently isolate the target signal from physiological noise remains the primary roadblock to regulatory approval and clinical adoption. Second, power supplying methods must be improved to provide a stable, high-density energy to enable active sensing and communication without external charging. Efficient energy harvesters and flexible, high-capacity energy storage and intelligent power management systems are required to respond to irregular energy inputs.[20,21] By solving emerging hardware and power management challenges, the next generation of wearable technology can be developed for decentralized, patient-centric healthcare.

Acknowledgments

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About the Authors

Min Ren received her M.S. degree from the School of Computing, Wuhan Institute of Technology, China, in 2010. She used to be a lecturer at Liaocheng University, Dongchang College, Shangdong, China. Since 2023, she has served as an associate professor at Liaocheng University, Dongchang College. Her research interests include computer applications, artificial intelligence, and image processing. (renmin@lcudcc.edu.cn)

Ning Du received his M.S. degree in communication and information systems from Chongqing University of Posts and Telecommunications, China, in 2008. He is currently pursuing his Ph.D. degree in systems engineering at the College of Electrical Engineering and Automation, Shandong University of Science and Technology, Qingdao, China. He also serves as a professor in the Department of Mathematics and Information Engineering at Liaocheng University, Dongchang College. His research interests include fifth-generation mobile communication systems, dynamic radio resource management, and cooperative communication. (duning@lcudcc.edu.cn)