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Emerging Piezoelectric Biomaterials for Advanced Medical Applications

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Advancement of AI-assisted self-powered healthcare sensing systems

Liwei Dong[a,b], Chaoyang Zhao[a], Chengjia Han[a], Yaowen Yang[a], Fan Yang[c,*]

Abstract

Self-powered sensors, which derive energy from environmental or physiological sources, provide a sustainable approach to eliminating the reliance on external power supplies. They enable the autonomous operation of sensing systems, paving the way for the increasingly expanding Internet of things (IoTs). The integration of artificial intelligence (AI) into these systems for healthcare has significantly advanced their capabilities in processing complex signals, extracting meaningful features, and delivering high-precision health insights. This review explores the latest advancement in self-powered sensors, involving the various applications of piezoelectricity, triboelectricity, electromagnetism, thermoelectricity, photovoltaics, and biofuel cells in healthcare. The applications of AI methodologies in self-powered sensing systems are covered and reviewed, addressing challenges like noise reduction, data analysis, and multisignal fusion. Future directions emphasize leveraging material innovation, manufacturing technology, structural optimization, and further integration of AI technology, to achieve multifunctional, high-performance, and intelligentized healthcare sensing systems. These developments underscore the potential of AI-assisted self-powered sensors to revolutionize healthcare with sustainable, precise, and intelligent solutions.

Keywords: Energy harvesting, Healthcare, Internet of things, Machine learning, Self-powered sensing

1. Introduction

In recent years, the rapid development of Internet of things (IoTs) and big data has significantly increased the need for sensors. Wearable sensors have emerged as a transformative technology, addressing the growing demand for personalized healthcare and human–machine interaction (HMI) through real-time monitoring of physiological states and motion.[1] These devices, which operate autonomously with integrated features of point-of-care systems and mobile connectivity, collect data noninvasively or minimally invasively to detect subtle physiological changes over time. Comprising key components such as substrate and electrode materials, sensing units for signal interfacing and transduction, decision-making units for data processing, and power units, wearable sensors provide precise and personalized health insights.[2] Their applications span health monitoring,[3] sports performance optimization,[4] and human–machine interaction[5] by measuring parameters like heart rate, blood pressure, and physical activity levels, enabling early detection and intervention to improve health outcomes and promote wellness. With the ability to deliver real-time feedback, these devices empower individuals to make informed decisions about their health and lifestyle, driving innovation and addressing modern challenges in healthcare and technology.

Self-powered sensing, which converts physiological signals into electrical signals through various energy conversion effects, significantly reduces the complexity of sensor implementation and enhances sensing system integration. The development of this technology can be divided into 3 stages. Before the 21st century, scientists discovered key energy conversion effects, such as piezoelectric,[6] triboelectrification, electromagnetic induction,[7,30–32] thermoelectric,[8] photovoltaic,[9,10] and electrochemical[11] effects, which formed the basis for self-powered sensing but lacked large-scale applications. From 2000 to 2020, advancements in flexible materials and fabrication processes greatly improved the flexibility, scalability, and biocompatibility of wearable sensors, leading to the emergence of numerous wearable applications.[12–21] Since 2020, breakthroughs in machine learning (ML) and deep learning (DL) have propelled the field into an era of artificial intelligence (AI)-driven self-powered sensing,[22–29] where customized sensor designs enhance electrical signal outputs under weak physiological conditions and advanced data processing enables the extraction of valuable features from complex and noisy signals. This has expanded applications in disease prevention, prediction, and rehabilitation. As a result, AI-integrated wearable sensing systems are becoming a key trend for intelligent healthcare applications (Figure 1).

Given the rapid advancements in AI technology and self-powered sensing systems, coupled with the growing demand for smart healthcare applications, we present a comprehensive review of AI-assisted healthcare self-powered sensing systems. Different from existing literature, this review emphasizes the

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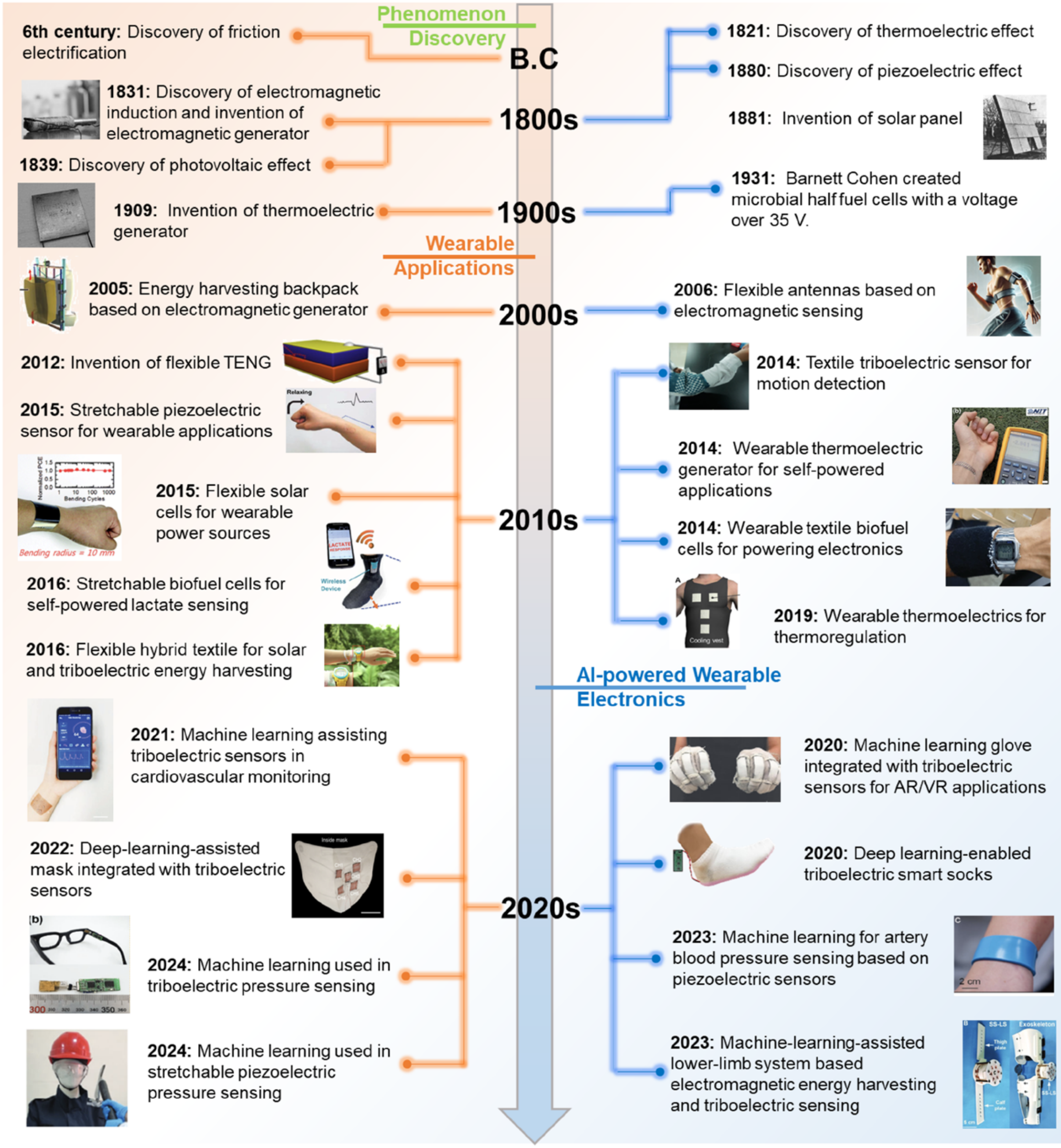

Figure 1. Advancement of self-powered sensing technology. Before the 21st century, scientists discovered key energy conversion effects, such as piezoelectric,[6] triboelectrification, electromagnetic induction,[7] thermoelectric,[8] photovoltaic,[9,10] and electrochemical[11] effects. From 2000 to 2020, advancements in flexible materials and fabrication processes greatly improved the flexibility, scalability, and biocompatibility of wearable sensors. In 2005, an energy-harvesting backpack based on an electromagnetic generator was invented. Adapted with permission from Rome et al,[12] Copyright © 2005, The American Association for the Advancement of Science. In 2006, flexible antennas based on electromagnetic sensing were designed.[13] In 2012, the first flexible triboelectric nanogenerator (TENG) was proposed. Adapted with permission from Fan et al,[14] Copyright © 2012 Elsevier Ltd. In 2014, a textile triboelectric sensor was developed for motion detection (adapted with permission from Zhou et al,[15] Copyright © 2014 American Chemical Society); a wearable thermoelectric generator was proposed for self-powered applications (adapted with permission from Kim et al,[16] Copyright © 2014 Royal Society of Chemistry); and wearable textile biofuel cells were developed for powering electronics (adapted with permission from Jia et al,[17] Copyright © 2014 Royal Society of Chemistry). In 2015, flexible solar cells were invented for wearable power sources. Adapted with permission from Kim et al,[18] Copyright © 2015 Royal Society of Chemistry. In 2016, stretchable biofuel cells were invented for self-powered lactate sensing (adapted with permission from Jeerapan et al,[19] Copyright © 2016 Royal Society of Chemistry); and a flexible hybrid textile was conceived for solar and triboelectric energy harvesting (adapted with permission from Chen et al,[20] Copyright © 2016, Springer Nature Limited). In 2019, wearable thermoelectrics were proposed for thermoregulation. Adapted with permission from Hong et al,[21] Copyright © 2019, The American Association for the Advancement of Science. Since 2020, breakthroughs in ML and DL have propelled the field into an era of AI-driven self-powered sensing. In 2020, an ML glove integrated with triboelectric sensors for augmented reality (AR)/ virtual reality (VR) applications was proposed (adapted with permission from Wen et al,[22] Copyright © 2020 Wiley-VCH GmbH); and DL-enabled triboelectric smart socks were invented (adapted with permission from Zhang et al,[23] Copyright © 2020 Springer Nature Limited). In 2021, ML-assisted triboelectric sensors were designed for cardiovascular monitoring. Adapted with permission from Fang et al,[24] Copyright © 2020 Wiley-VCH GmbH. In 2022, a DL-assisted mask was designed and integrated with triboelectric sensors. Adapted with permission from Fang et al,[25] Copyright © 2022 Wiley-VCH GmbH. In 2023, ML was proposed for artery blood pressure sensing based on piezoelectric sensors (adapted with permission from Li et al,[26] Copyright © 2023 Springer Nature Limited); and an ML-assisted lower-limb system-based electromagnetic energy-harvesting and triboelectric sensing was designed (adapted with permission from Kong et al,[27] Copyright © 2023 Wiley-VCH GmbH). In 2024, ML was used in triboelectric pressure sensing (adapted with permission from Xie et al,[28] Copyright © 2024 Wiley-VCH GmbH); and ML was employed in stretchable piezoelectric pressure sensing (adapted with permission from Garg et al,[29] Copyright © 2024 Wiley-VCH GmbH).

materials, manufacturing processes, structural designs, and integrated approaches specific to healthcare systems based on various self-powered sensing principles. Additionally, we explore in depth the role of AI technology in enhancing these systems, driving automation and intelligence in healthcare applications. First, we introduce the principles and foundational development of self-powered sensing technology. Next, we review its applications in the healthcare field, emphasizing materials, manufacturing processes, and structural designs. Furthermore, we summarize and examine the role of AI in sensing systems, as well as its combination with signal recognition, classification, and disease rehabilitation. Finally, we discuss the challenges faced by self-powered sensing systems and explore potential future directions for their development.

2. Principle of self-powered sensing

Energy harvesting technologies have emerged as a key solution for self-powered sensors by utilizing ambient or body-derived energy. Energy harvesting mechanisms (Figure 2), including piezoelectricity, triboelectricity, electromagnetic radiation, thermoelectricity, photovoltaics, and electrocatalytic reaction, are widely explored for self-powered applications.

Piezoelectric sensors utilize mechanical stress or strain to create an internal electric field within piezoelectric materials (Figure 2A).[33–36] Common materials include zinc oxide nanorods, lead zirconate titanate (PZT), barium titanate ($BaTiO_3$), and polyvinylidene fluoride (PVDF), which are structured to maximize energy conversion efficiency.[37–39] With power densities reaching up to 810 mW/m²,[40] these systems are effective for capturing energy from low-frequency movements. Piezoelectric sensors have better stability and are less susceptible to external environmental interference. They can be classified into compression type and bending type, utilizing the d33 and d31 piezoelectric modes, respectively. The d33 mode is typically employed to measure small-displacement press or pulse signals, while the d31 mode is more suited for monitoring large-displacement joint motion.

Triboelectric sensors operate based on the triboelectric effect and electrostatic induction (Figure 2B). When two materials with different electron affinities come into contact, electrical charges are generated on their surfaces. Upon separation, charges are induced at the electrodes, allowing charge flow between them due to electrostatic induction.[14,41,42] A key advantage of triboelectric sensors is the wide availability of triboelectric materials. The selection of suitable materials can be guided by the triboelectric series.[43] In general, materials containing fluorine exhibit a strong ability to attract negative charges, such as polytetrafluoroethylene (PTFE), polydimethylsiloxane (PDMS), and fluorinated ethylene propylene (FEP). Conversely, materials such as aluminum (Al), copper (Cu), nylon, and glass, tend to lose electrons easily, becoming positively charged. The design of triboelectric sensors should ensure that the selected materials have significantly different charge-attracting capabilities to optimize performance.[44] Triboelectric sensors operate in four fundamental modes: contact-separation mode, single-electrode mode, lateral-sliding mode, and freestanding triboelectric-layer mode.[43] The contact-separation and single-electrode modes promote full contact between surfaces, maximizing charge transfer, making them particularly suitable for mechanical vibration energy harvesting.[45] In contrast, the lateral-sliding and freestanding triboelectric-layer modes minimize surface contact to reduce friction and wear, making them ideal for applications involving rotary motion, such as harnessing wind[46] and water flow[47] energy with high efficiency. Furthermore, triboelectric generators (TENGs) offer power densities of up to 10 W/m²[48]

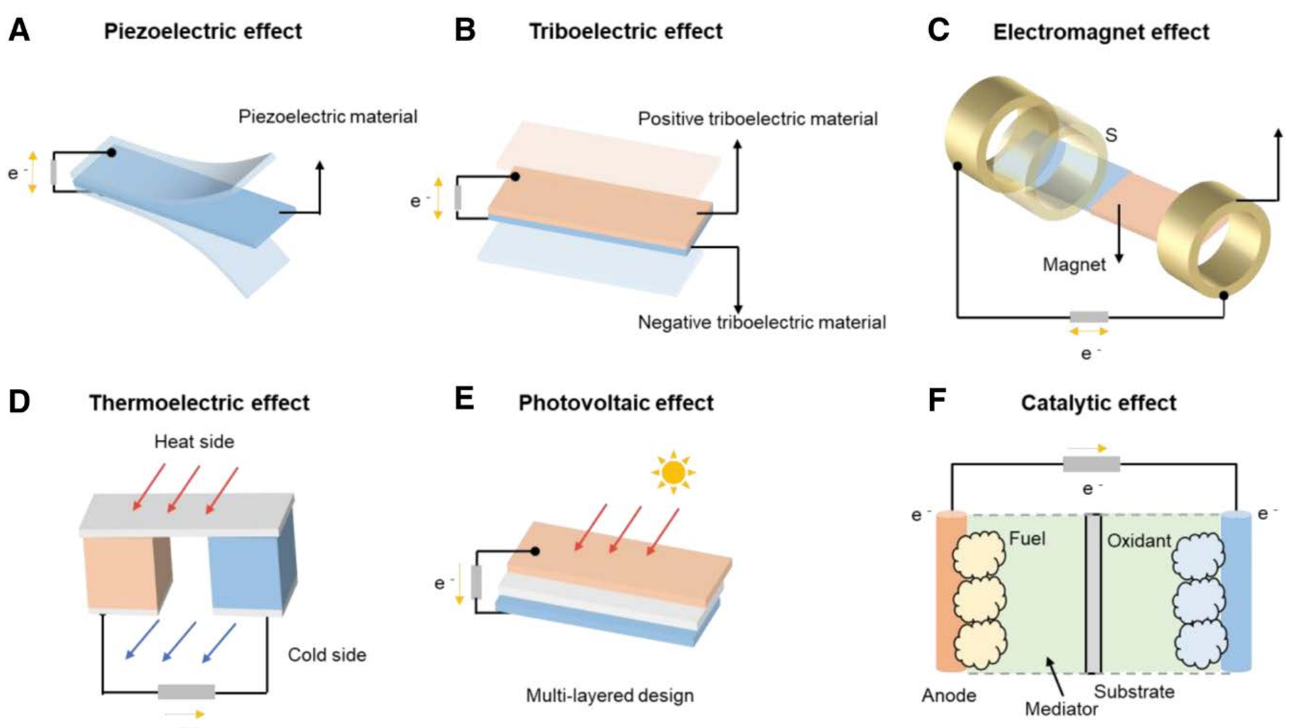

Figure 2. Principles of self-powered sensing. (A) Piezoelectric effect. (B) Triboelectric effect. (C) Electromagnet effect. (D) Thermoelectric effect. (E) Photovoltaic effect. (F) Catalytic effect.

and are flexible enough for integration into textiles or on-skin applications. As sensing devices, TENGs are highly sensitive and can generate significant voltages under weak physical inputs. However, durability remains a concern, as many TENGs rely on metallic-organic polymers prone to degradation over time.[49]

Electromagnetic induction offers a promising way for healthcare sensing, as flexible antennas can capture ambient electromagnetic waves for both power and data transfer without batteries (Figure 2C).[50,51] These antennas are made from materials like polymers, textiles, graphene, neoprene, wool, cellulose, and silk and composites such as ceramics or MXenes.[52] A key challenge is ensuring the substrates are printable, with conductive materials like Cu or special inks used.[53] Research is ongoing to investigate on new materials and physical effects to improve the performance.[54,55] Wearable antennas are compact and operate at frequencies of GHz.[56] They are useful for tracking body movement and position, such as walking, falling, or bending, making them ideal for health and activity monitoring.[57,58] However, challenges include how the antenna interacts with the human body, which can affect performance, especially with high electromagnetic exposure.[59] Antennas also need to withstand deformation from movements like walking or bending and maintain stable performance over time, despite environmental factors like temperature, humidity, and frequent washing.

Thermoelectric generators (TEGs) harness small amounts of heat and convert them into electricity (Figure 2D), making them ideal for powering wearable devices by utilizing heat generated through human metabolic activities. These generators offer the potential for near-perpetual energy production.[60] While traditional TEGs are typically rigid and bulky, recent advancements have introduced flexible versions made from composite materials, including conductive polymers, hybrid organic–inorganic materials, continuous inorganic films, and liquid metals, which are better suited for wearable applications.[61,62] However, these devices often resemble heatsinks, making them difficult to clean and less aesthetically appealing. In comparison to piezoelectric nanogenerators (PENGs) and TENGs, TEGs tend to be larger in size, typically measuring tens of square centimeters, and have lower power densities of up to 400 mW/m^2.[63] Despite their potential, several challenges remain in the development of stable and efficient wearable TEGs. These include low energy conversion efficiency, issues with biocompatibility, maintaining consistent contact with the heat source, and ensuring adaptability to changes in body temperature across different environments.[64]

Photovoltaic materials represent a sustained energy source for wearable sensors, offering the advantage of solar power harvesting (Figure 2E). Traditionally, solar cells are rigid; however, recent innovations have led to the development of stretchable, twistable, and bendable photovoltaic devices based on transparent electrodes or smart textiles made from deformable hybrid thin films and soft composite materials.[65] These smart textiles enable photorechargeable power sources, some of which are even washable.[66,67] However, miniaturization remains a significant challenge for solar cells, as they tend to be bulky and heavy, particularly for applications requiring higher energy densities. Additionally, much of the space in wearable devices is occupied by energy storage components, which limits the potential for compact, lightweight designs. Solar cells convert sunlight into electricity using multilayered photovoltaic materials. Stretchable, bendable, and washable designs have been achieved through advanced materials like transparent electrodes and deformable hybrid films. While solar energy is a promising renewable source, these systems often remain bulky and require further miniaturization to meet the size and energy density demands of wearable devices.[68]

Biofuel cells offer a promising power source for wearable sensors by using enzymes to convert chemical energy into electricity (Figure 2F). For example, lactate, which is abundant in sweat, can be used as a fuel. Enzymes such as lactate oxidase can oxidize lactate to generate electricity.[69] Biofuel cells can also use other substances in sweat, such as glucose, urea, and ammonium, allowing for multianalyte detection.[70,71] This makes them ideal for self-powered wearables that monitor health. However, challenges include improving energy density, catalyst stability, fuel availability, and miniaturization.[72] Enzyme degradation under nonideal conditions can reduce performance, but nanozymes, as catalytically active nanoparticles with enzyme-like kinetics, have shown potential as replacements.[73] Incorporating nanomaterials like carbon nanotubes (CNTs) and high-surface-area electrodes can boost efficiency.[74] Current wearable biofuel cells are advantageous in size and can deliver power densities of mW/cm^2.[75]

3. Self-powered sensing for healthcare

3.1 Piezoelectric sensors

The evolution of wearable piezoelectric sensors has been significantly influenced by the continuous innovation in piezoelectric materials. These materials play a pivotal role in translating mechanical stimuli into electrical signals, enabling diverse applications in health monitoring, energy harvesting, and HMI.

Inorganic piezoelectric materials, such as PZT and $BaTiO_3$,[76,77] have long been favored for their high piezoelectric coefficients and robustness in energy conversion. However, they are inherently rigid, brittle, and difficult to process, limiting their applications in wearable devices. Piezoelectric polymers, such as PVDF and its copolymers, have gained prominence due to their intrinsic flexibility, lightweight nature, and processability.[78] Among these, PVDF exhibits a piezoelectric coefficient d_{33} of approximately ~23 pC/N when well-electrically poled. Copolymers of PVDF, such as polyvinylidene fluoride-trifluoroethylene (PVDF-TrFE), offer an enhanced d_{33} of ~40 pC/N.[79,80]

One significant direction involves optimizing PVDF-based composites to enhance the β-phase content, a critical factor in improving piezoelectric performance. Zhang et al[81] incorporated $BiCl_3$ and ZnO into electrospun PVDF nanofibers, achieving a longitudinal piezoelectric coefficient of 3.8 pC/N. The resulting hybrid nanofiber-based PENGs demonstrated sensitivity in detecting human joint movements, such as elbow and knee bending. Similarly, Li et al[82] developed $BaTiO_3$-doped PVDF nanofibers, as shown in Figure 3A, which exhibited enhanced β-phase content and durability over 12,000 loading cycles. Their self-powered tactile sensor showed high sensitivity and repeatability for detecting human motion, making it suitable for healthcare and activity-tracking applications.

Efforts to improve piezoelectric polymers also extend to self-poling methods, which eliminate the need for energy-intensive electrical poling. As illustrated in Figure 3C, Huang et al[84] introduced a melt-state energy implantation technique to fabricate PVDF/$BaTiO_3$ composites, achieving a high d_{33} value of 51.20 pC/N. This method simplifies the production process while enabling sustainable self-powered sensing and energy harvesting.

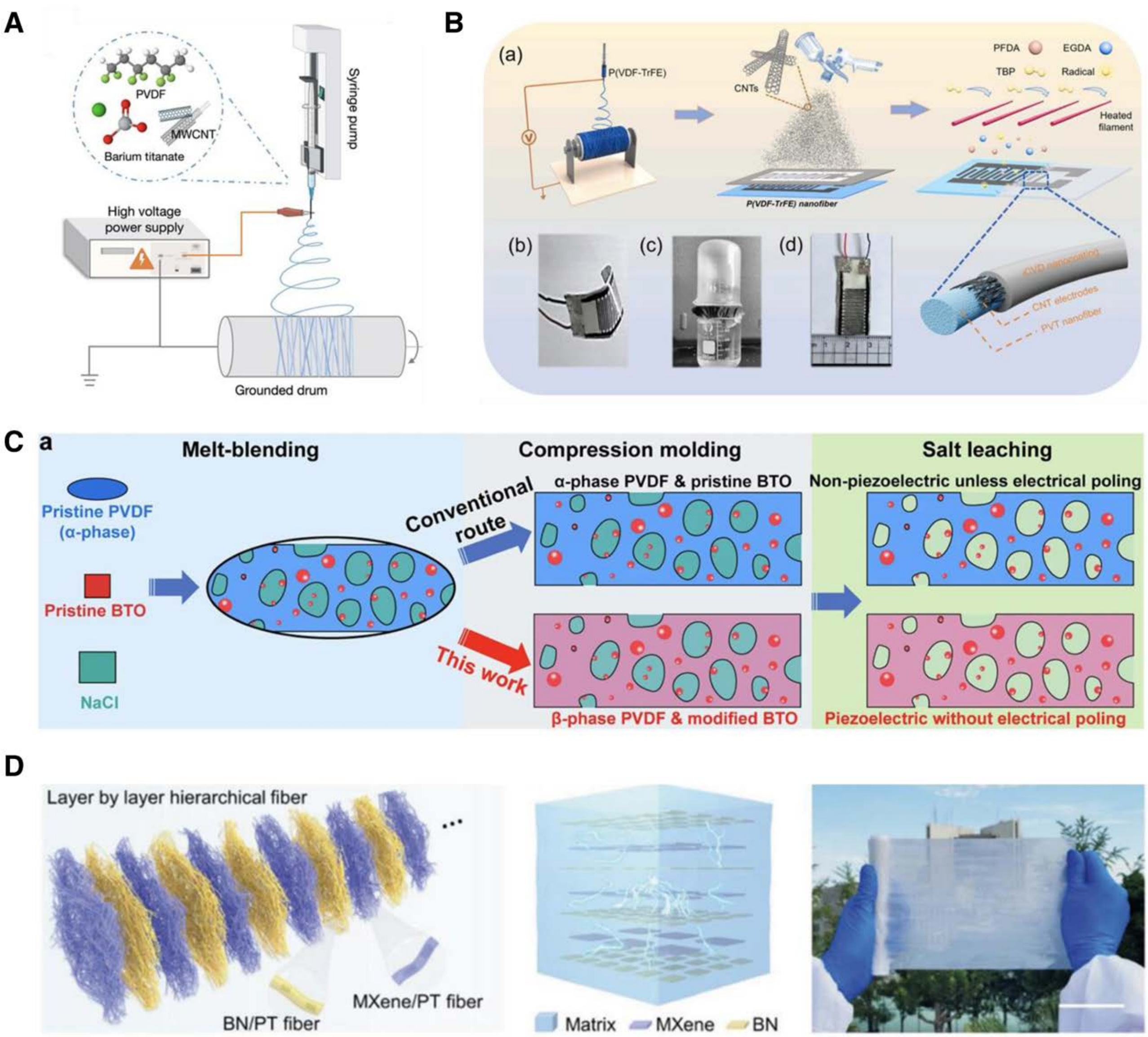

Figure 3. Progress in piezoelectric sensors from a material perspective. (A) Electrospinning process of $BaTiO_3$-doped PVDF nanofibers. Adapted with permission from Li et al,[82] Copyright © 2023, Donghua University. (B) Preparation process of piezoelectric sensor with a superhydrophobic coating. Adapted with permission from Su et al,[83] Copyright © 2022, Elsevier Ltd. (C) Fabrication process of PVDF/$BaTiO_3$ composites. Adapted with permission from Huang et al,[84] Copyright © 2024 Springer Nature Limited. (D) Illustration of the hierarchical piezoelectric composite film. Adapted with permission from Tian et al,[85] Copyright © 2024 Wiley-VCH GmbH.

To overcome the inherent limitations of polymer-based piezoelectric materials, hybrid composites integrating ceramic fillers have been widely studied. Du et al[86] developed multilayered PZT/PVDF composites with a porous structure, which enhanced overall polarization and surface charge density. The resulting PENG achieved an output voltage of 62 V, a significant improvement compared with traditional composites, and demonstrated excellent flexibility and mechanical robustness. In a complementary approach, Tian et al[85] utilized MXene and boron nitride nanosheets within PVDF-TrFE composites, as depicted in Figure 3D, achieving a piezoelectric charge coefficient of 41.67 pC/N. These hierarchical composites were optimized for continuous blood pressure monitoring, offering both accuracy and user comfort in wearable applications.

Inorganic materials have also been explored for their superior piezoelectric properties and stability. Lv et al[87] developed an all-inorganic Sm-doped PMN-PT thin film on a flexible mica substrate, achieving an ultrahigh d_{33} value of 380 pm/V. This material enabled devices with exceptional energy-harvesting performance and motion-sensing capabilities, further demonstrating the potential of flexible inorganic piezoelectric films in advanced wearable technologies.

To address environmental durability and long-term usability, researchers have investigated surface treatments and encapsulation methods. Venkatesan et al[88] combined perovskite quantum dots with PVDF nanofibers, achieving a high open-circuit voltage of 20.3 V while incorporating photocatalytic functionalities for environmental applications. Moreover, the durability and environmental resistance of wearable devices have been significantly improved by surface modifications. As shown in Figure 3B, Su et al[83] introduced a superhydrophobic coating via initiated chemical vapor deposition on piezoelectric sensors, enhancing their resistance to humidity, liquid exposure, and bacterial fouling. This innovation ensures stable and reliable performance in harsh environments, demonstrating the practical viability of wearable piezoelectric sensors in real-world applications.

Advancements in the structural design of piezoelectric wearable sensors have played a critical role in enhancing their functionality, sensitivity, and durability from another perspective. These innovations focus on bioinspired structures, novel geometries, and multifunctional integration to address challenges such as adaptability, mechanical stability, and multienvironment operability.

Bioinspired designs have emerged as a powerful approach to enhancing the sensitivity and adaptability of piezoelectric sensors. As shown in Figure 4A, Yuan et al[89] introduced a bionic lateral-line–inspired sensor, mimicking the stress-concentration mechanism of fish. The curved PVDF-based structure demonstrated an exceptionally low detection limit of 0.0005 N, enabling highly sensitive respiratory monitoring. He et al[90] drew inspiration from the cuttlebone structure, designing a 3D-printed composite reinforced with Rochelle salt crystals, as illustrated in Figure 4B. This structure achieved a balance between mechanical protection and piezoelectric sensitivity, making it ideal for high-impact applications such as sports monitoring and fall detection systems. Both studies highlight how nature-inspired structural features can be translated into advanced sensor designs with enhanced performance.

The optimization of mechanical deformations has also been a significant direction in structural design. As illustrated in Figure 4C, Zhou et al[91] employed a 3D-printed auxetic structure to transform bending deformations into in-plane stretching, amplifying piezoelectric output by 8.3 times. This structure enables efficient energy-harvesting and precise motion sensing, demonstrating the potential of structural design to expand the mechanical adaptability of piezoelectric devices. Similarly, Wu et al[92] incorporated microcavities into the piezoelectric layer to improve sensitivity and durability, as illustrated in Figure 4D. This design allowed for real-time dynamic pressure monitoring, including applications in robotics and prosthetics.

Integrating multifunctionality into structural designs has been another key focus. Zhang et al[93] developed a flexible lamb wave-based piezoelectric device capable of sensing, communication, and positioning. This multifunctional system combines high-frequency acoustic sensing for respiratory monitoring with

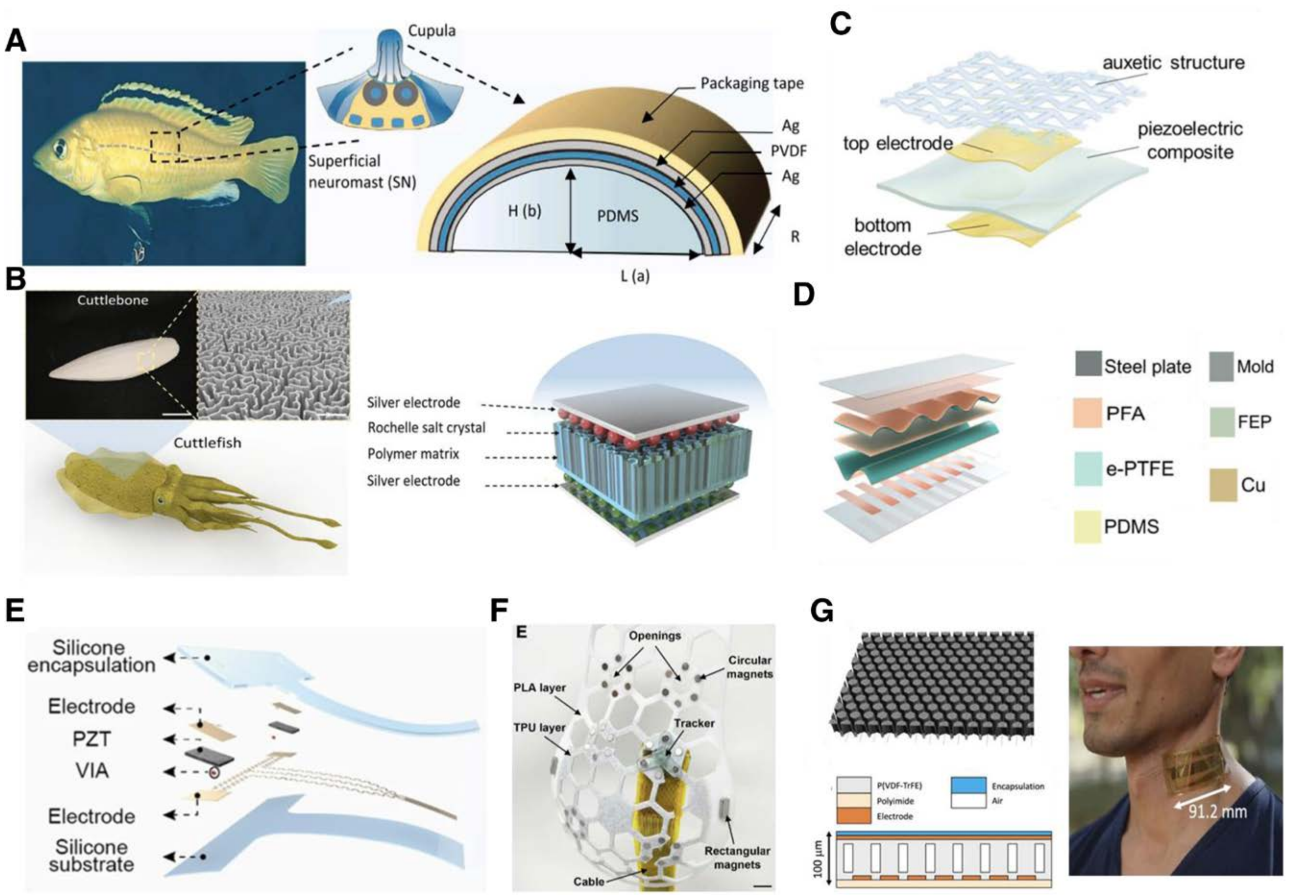

Figure 4. Progress in piezoelectric sensors from a structural perspective. (A) Bionic lateral-line-inspired piezoelectric sensor. Adapted with permission from Yuan et al,[89] Copyright © 2022, Elsevier Ltd. (B) Cuttlebone-inspired piezoelectric sensor. Adapted with permission from He et al,[90] Copyright © 2023 Springer Nature Limited. (C) Piezoelectric sensor with 3D-printed auxetic structure. Adapted with permission from Zhou et al,[91] Copyright © 2023 Wiley-VCH GmbH. (D) Piezoelectric sensor with microcavities enhancing sensitivity. Adapted with permission from Wu et al,[92] Copyright © 2024 Wiley-VCH GmbH. (E) Thin, soft piezoelectric sensor array for blood pressure monitoring. Adapted with permission from Li et al,[26] Copyright © 2023 Springer Nature Limited. (F) Honeycomb-structured patch for breast cancer diagnostics. Adapted with permission from Du et al,[96] Copyright © 2023, The American Association for the Advancement of Science. (G) Ultrasound transducer foil-based embossed polymer. Adapted with permission from van Neer et al,[95] Copyright © 2024 Springer Nature Limited.

low-frequency vibration for wireless communication. The integration of diverse functionalities into a single device underscores the versatility of structural innovations in piezoelectric sensors.

In healthcare, structural innovations have been pivotal in achieving accurate and continuous monitoring. Yi et al[94] optimized piezoelectric dynamics for arterial pulse monitoring, addressing challenges in fidelity and motion artifacts. Their single-sensor system achieved precise continuous blood pressure monitoring, providing a simpler and more portable alternative to conventional multisensor setups. As depicted in Figure 4E, Li et al[95] expanded on this by integrating a thin, soft piezoelectric sensor array into an ML-assisted system for continuous arterial blood pressure monitoring. This conformal design improves skin interaction and enhances measurement accuracy, marking a significant step forward in wearable medical technologies.

For imaging applications, ultrasound-based piezoelectric devices have seen remarkable advancements. Du et al[96] introduced a honeycomb-structured patch for breast cancer diagnostics (Figure 4F), achieving precise imaging over large, curved surfaces. Van Neer et al[26] developed an embossed polymer ultrasound array for flexible medical imaging (Figure 4G). By eliminating rigid transducer assemblies, their design enables scalable, high-performance patches for real-time monitoring of organs and blood flow. These studies demonstrate the transformative potential of structural innovations in wearable imaging technologies.

Overall, the continuous innovations in piezoelectric materials and structural designs have significantly advanced the capabilities of sensors. By addressing challenges related to flexibility, biocompatibility, and sustainability, they have paved the way for multifunctional, self-powered, and user-friendly wearable technologies.

3.2 Triboelectric sensors

Triboelectric sensors offer real-time, noninvasive monitoring of physiological and biomechanical parameters. By utilizing the triboelectric effect, these sensors convert mechanical stimuli, such as motion, pressure, or strain, into electrical signals, enabling precise measurements of athletic performance, injury risk, and rehabilitation progress.[97–99] A key advantage of triboelectric sensors is their ability to generate electrical signals autonomously, eliminating the need for external power sources. Many researchers have focused on designing sensors using textiles and fabrics due to their comfort and practicality in real-world applications. For instance, Fang et al[24] introduced a textile-based triboelectric sensor composed of a PDMS substrate, FEP film, Al, CNTs conductive layers, and packaging textile. This sensor demonstrates high sensitivity with a signal-to-noise ratio of 23.3 dB and a response time of 0.21 μA/kPa, enabling accurate blood pressure measurement and monitoring the progression of atherosclerosis in blood vessels, as illustrated in Figure 5A. Additionally, the sensor operates effectively under various environmental conditions, including stationary, dynamic, and humid settings. Wen et al[100] reported a self-powered textile by integrating fiber-shaped triboelectric nanogenerators, solar cells, and supercapacitors as shown in Figure 5B. This innovative design combines energy generation and storage capabilities, resulting in a compact and efficient system. Similarly, other fiber-based textile sensors have been developed, as reported by Yu et al[101] and Kim et al.[102] Most of these fibers are either composed of polymers or coated with elastomers such as PDMS to enhance flexibility.[103] However, while PDMS provides good flexibility and stretchability, its poor breathability can lead to skin-related issues. To address this limitation, fabric-based designs have been explored. Choi et al[104] developed a corrugated textile-based TENG using a knitted conductive textile, a layer of silicone rubber, and woven silk coated with conductive textile, as shown in Figure 5C. This generator effectively produces energy through pressing and stretching motions. Chu et al[105] fabricated a conformal TENG using PEF fabric as a substrate, with graphene as the electrode for enhanced performance (Figure 5D). Xiong et al[106] designed an all-fabric-based triboelectric sensor utilizing hydrophobic cellulose oleoyl ester nanoparticles (HCOENPs), as illustrated in Figure 5E. This sensor not only exhibits excellent waterproofing properties but also generates electricity from water droplets, achieving a power density of 0.14 W/m^2.

Triboelectric sensors are highly effective for monitoring human motion, with the most typical structure consisting of two contact layers. For example, Chen et al[107] introduced a sensor based on crumpled gold films. In this design, gold is deposited onto a prestretched elastomer. When the applied force is released, the surface buckles, forming a crumpled structure. This phenomenon enhances the effective contact area between the triboelectric layers, improving the sensor's performance. The sensor is capable of monitoring finger bending angles and gestures with precision, as depicted in Figure 5F. Significant attention has been directed toward designing sensors for monitoring the motion of body joints, such as fingers,[108] wrists,[109] elbows,[110] and knees.[111] These designs aim to capture the full-body motion status through advanced signal processing and analytical methods. To ensure accurate monitoring of joint movements, researchers are innovating sensor structures to improve functionality. For instance, Zhu et al[112] reported a bidirectional triboelectric sensor integrated into a sensory system capable of detecting multiple degrees of freedom. This sensor is suitable for incorporation into exoskeleton systems to facilitate robotic manipulation. Figure 5G shows the working mechanism of the triboelectric sensing unit, featuring a circular grating pattern made from PTFE film and a cam-shaped switch with electrodes. The rotation angle is determined by counting the generated pulses, while the rotation direction is also detectable.

TENGs can also serve as power sources and integrate seamlessly with other sensors. For example, Song et al[113] developed a self-powered wearable sensor for human motion monitoring. This sensor incorporates a microfluidic sweat sensor powered by a flexible printed circuit board (FPCB)-based freestanding triboelectric nanogenerator (FTENG). The FTENG incorporates a grating structure composed of an FPCB stator and sliders, with the stator surface laminated with PTFE, as shown in Figure 5H. The system's circuitry is integrated into the FPCB, providing both flexibility and comfort when attached to human skin. Additionally, the monitored signals are designed for seamless wireless transmission to mobile devices. For comprehensive medical applications, a systematic design is essential when integrating triboelectric harvesters with other sensors. This requires both the harvesters and sensors to be flexible, lightweight, and compact. Such demands have further driven advancements in soft electronics, offering innovative solutions for wearable technologies.[114] In summary, the wearable design of triboelectric sensors makes them ideal for integration into sports gear, enabling continuous data acquisition without hindering movement. Furthermore, their high sensitivity and self-powered operation minimize the need for external power sources, enhancing their practicality for long-term use.

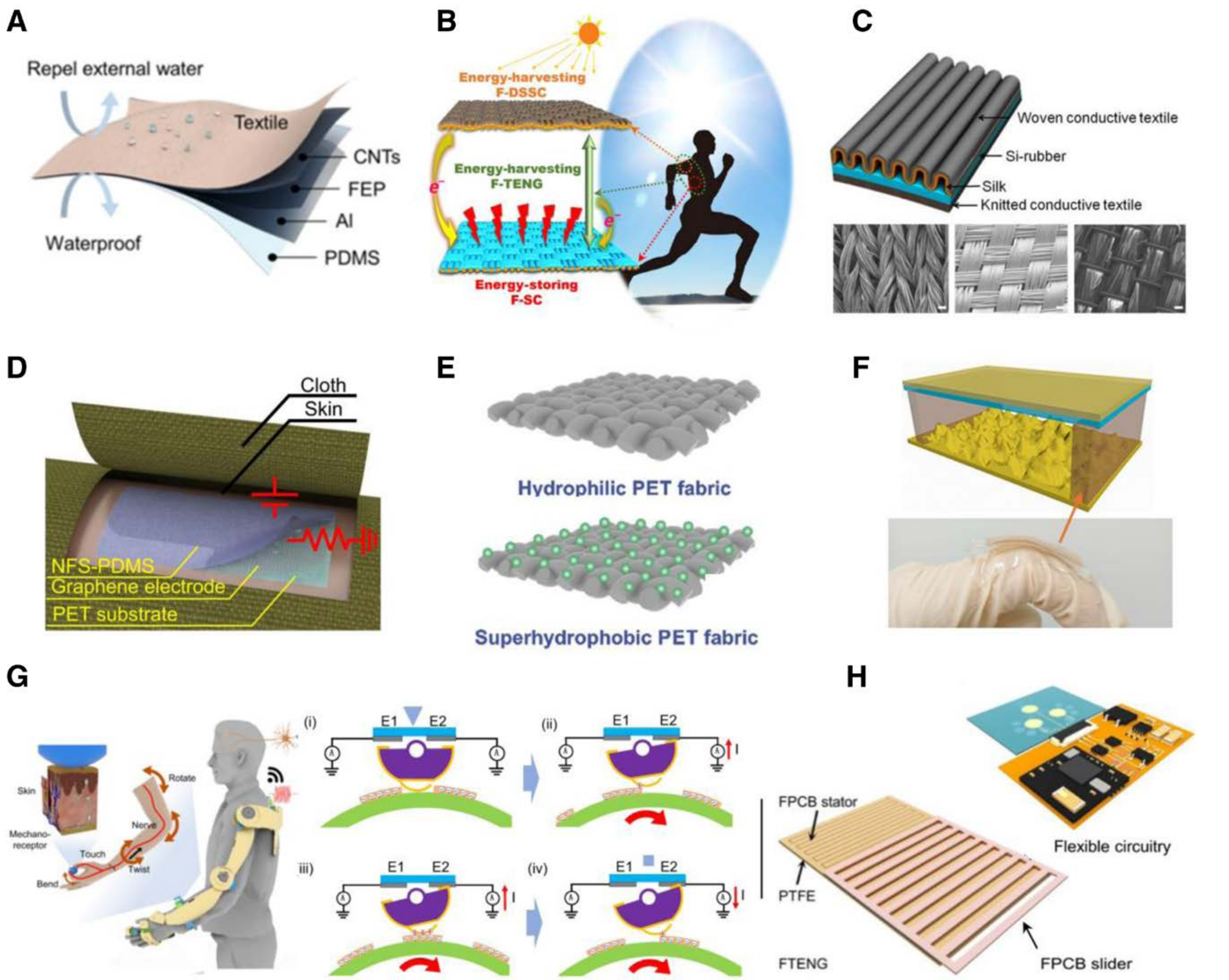

Figure 5. Progress in triboelectric sensors. (A) Photograph of the single-layered ultra-soft smart textile. Adapted with permission from Fang et al,[24] Copyright © 2020 Wiley-VCH GmbH. (B) Schematic illustration of fiber-based self-powered system. Adapted with permission from Wen et al,[100] Copyright © 2016, The American Association for the Advancement of Science. (C) Corrugated textile-based TENG and its microscale morphology. Adapted with permission from Choi et al,[104] Copyright © 2017, Springer Nature Limited. (D) Conformal triboelectric sensor attached to the human skin. Adapted with permission from Chu et al,[105] Copyright © 2016, Elsevier Ltd. (E) Diagram of hydrophobic PET fabric with HCOENPs coating. Adapted with permission from Xiong et al,[106] Copyright © 2017 Wiley-VCH GmbH. (F) Crumpled Au-based triboelectric sensor to monitor finger motion. Adapted with permission from Chen et al,[107] Copyright © 2018, Elsevier Ltd. (G) Schematics of exoskeleton sensory system and working principle of triboelectric sensor. Adapted with permission from Zhu et al,[112] Copyright © 2021, Springer Nature Limited. (H) Schematic diagram of the FPCB-based FTENG with a grating slider and stator, which is integrated into microfluidic-based sweat sensor patch interfacing with the flexible circuitry. Adapted with permission from Song et al,[113] Copyright © 2020, The American Association for the Advancement of Science.

3.3 Thermoelectric generators

TEGs convert temperature gradients into electrical signals, providing valuable insights into an athlete's health, performance, and recovery. Their lightweight, flexible, and noninvasive design allows seamless integration into wearable devices or sports gear, ensuring comfort and minimal interference with movement.[122–124] A typical TEG functions like a band-aid, providing adaptability to human skin. For example, Sattar et al[115] reported an all-in-one flexible thermoelectric device capable of measuring multiple physiological signals, such as electrocardiograms (ECGs), heart rate variability, and electromyograms (EMGs), in real-time. The TEG, shown in Figure 6A, is constructed from highly thermal-conductive CNT film with the surface-constructed thermal p/n junction components. A Cu heat sink layer enhances heat rejection, maintaining a high thermal gradient. The thermoelectric unit can be integrated with bioelectrical sensors. Yang et al[116] reported a similar type of TEG with integrated electronics capable of generating electricity from body heat, as illustrated in Figure 6B. However, such TEGs typically require the assembly of rigid p/n junctions, which compromises their flexibility and comfort. To address the challenges, Karthikeyan et al[117] developed a film-type thermoelectric energy generator by depositing N-PbTe and P-SnTe arrays onto a polyimide substrate, as displayed in Figure 6C. This generator achieved a maximum output voltage and power density of 250 mV and 8.4 mW/cm^2, respectively, at a temperature gradient of 120°C.

To further enhance flexibility, fiber-type thermoelectric components have been investigated. For example, Ding et al[118] developed scalable thermoelectric fibers for multifunctional textile electronics. As shown in Figure 6D, the p-n gel segments are fabricated using an alternating extrusion process, enabling

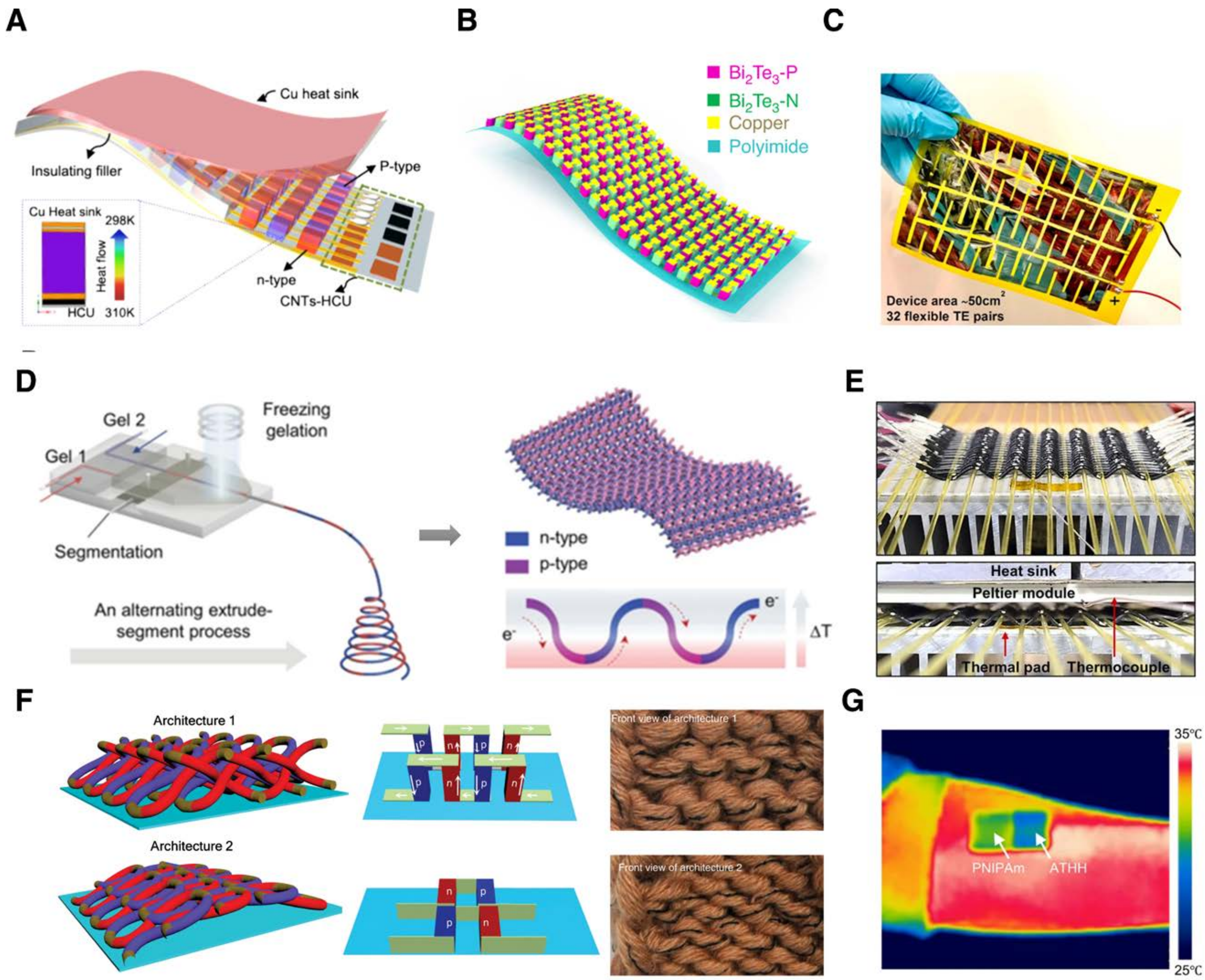

Figure 6. Progress in TEGs. (A) A typical flexible thermoelectric unit. Adapted with permission from Sattar et al,[115] Copyright © 2024 American Chemical Society. (B) Diagram of TEG with P/N Bi_2Te_3 on the polyimide substrate. Adapted with permission from Yang et al,[116] Copyright © 2023, Springer Nature Limited. (C) Actual photo of TEG with 32 pairs. Adapted with permission from Karthikeyan et al,[117] Copyright © 2020, Elsevier Ltd. (D) Diagram of alternating extrusion process for thermoelectric fiber fabrication and detailed textile with the pitch waves showing successive p-n junctions alternate between hot and cold surfaces. Adapted with permission from Ding et al,[118] Copyright © 2020, Springer Nature Limited. (E) Weaved fabric and the test setup for evaluating its thermoelectric performance. Adapted with permission from Jang et al,[119] Copyright © 2022, Elsevier Ltd. (F) Illustration of two different fiber assembly architectures on the actual fabric. Adapted with permission from Sun et al,[120] Copyright © 2020, Springer Nature Limited. (G) Infrared radiation camera image of autonomous thermal homeostatic hydrogel on a human skin. Adapted with permission from Park et al,[121] Copyright © 2023, Springer Nature Limited.

continuous meter-scale thermoelectric fiber production with clear p-n gel interfaces. These fibers can be woven into flexible thermoelectric textiles for conformable heat energy harvesting and to power biomedical sensors. Similarly, Jang et al[119] introduced a 3D thermoelectric fiber with exceptional mechanical reliability and an elongation ratio of up to 100% (Figure 6E). Furthermore, to improve the comfort and breathability of thermoelectric sensors, Sun et al[120] developed active thermoelectric materials using carbon nanotube fibers, which were strategically woven into stretchable fabrics, as indicated in Figure 6F. This design demonstrated a peak power density of 70 mW/m², providing enhanced wearability and performance.

Beyond fibers and fabrics, hydrogels have emerged as promising materials for thermoelectric applications due to their high-water content, biocompatibility, and ability to interface seamlessly with biological tissues. Thermal homeostasis, a critical physiological function maintaining the body's optimal temperature of 36 to 37°C, can also be effectively addressed using hydrogel-based materials. Park et al[121] introduced an autonomous thermal homeostatic hydrogel (ATHH) capable of reversible and bidirectional thermal control. Fully attachable to the skin, the ATHH effectively blocks infrared radiation from the body, as depicted in Figure 6G. Further studies confirmed that the ATHH generates electrical signals corresponding to temperature changes, demonstrating its potential for energy-harvesting and biosensing applications. Overall, thermoelectric sensors harness body heat to generate continuous power, offering a distinct advantage over piezoelectric and triboelectric sensors, which rely on mechanical motion.

3.4 Solar cells

Solar cells convert light energy into electrical signals to power wearable electronics or monitor environmental factors. They are widely employed in applications such as tracking heart rate, oxygen saturation, and skin temperature, often through wearable devices.[125–127] Min et al[128] introduced a highly integrated wearable biosensor powered by a flexible perovskite solar

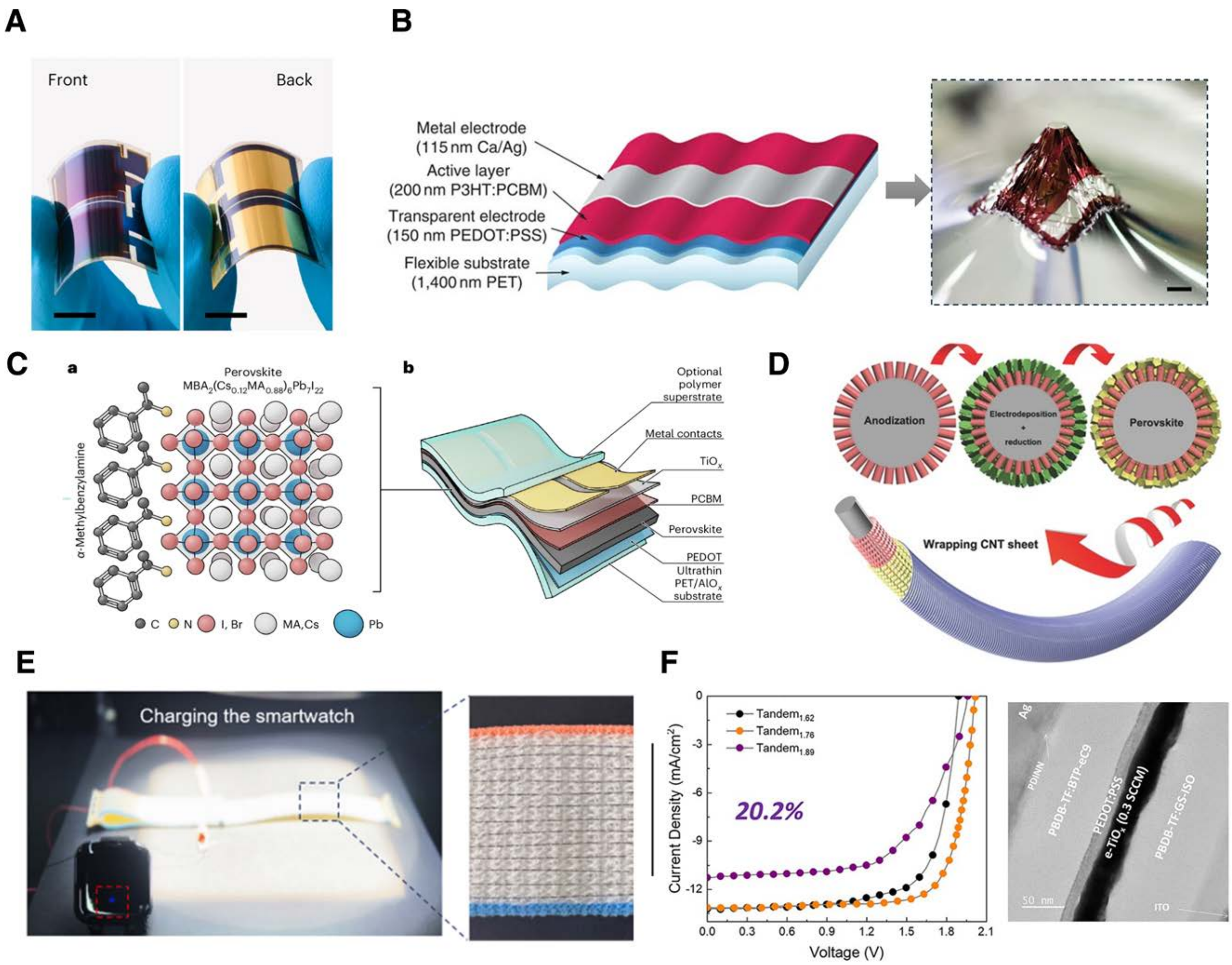

Figure 7. Progress in solar cells. (A) Photo of an FPSC. Adapted with permission from Min et al,[128] Copyright © 2023, Springer Nature Limited. (B) Diagram of the ultra-light and flexible organic solar cell and the deformed device attached to the elastomeric support. Adapted with permission from Kaltenbrunner et al,[129] Copyright © 2012, Springer Nature Limited. (C) Schematic illustration of the perovskite device architecture and the photo of an actual flexible solar cell. Adapted with permission from Hailegnaw et al,[130] Copyright © 2024, Springer Nature Limited. (D) Diagram of solar cell in fiber shape. Adapted with permission from Qiu et al,[132] Copyright © 2016, Wiley-VCH GmbH. (E) Actual photos of the organic solar cell integrated into the fabric. Adapted with permission from Lv et al,[133] Copyright © 2022, Springer Nature Limited. (F) Graph showing the efficiency of organic solar cell and its corresponding cross-sectional scanning electron microscope (SEM) image. Adapted with permission from Zheng et al,[135] Copyright © 2022, Cell Press.

cell (FPSC) as depicted in Figure 7A. This compact FPSC functions as a power source and integrates with biosensor arrays to monitor various physicochemical markers, including glucose, pH, Na+, sweat rate, and skin temperature. For optimal performance, solar cells must exhibit high energy conversion efficiency while maintaining flexibility and comfort to adapt seamlessly to human skin. Kaltenbrunner et al[129] reported ultrathin and lightweight organic solar cells with remarkable flexibility. Figure 7B shows the cell's multilayer structure, with a total thickness of just 1.9 μm. These cells deform along with a bonded elastomeric substrate, demonstrating exceptional conformability. Similarly, Hailegnaw et al[130] developed flexible quasi-2D perovskite solar cells characterized by high specific power and improved stability. Figure 7C shows a multilayer structure and a thickness of less than 2.5 μm. These cells are flexible yet resistant to buckling, which can adversely affect power conversion efficiency. These advanced cells achieved an outstanding specific power of 44 W/g (average: 41 W/g), an open-circuit voltage of 1.15 V, and a champion efficiency of 20.1% (average: 18.1%). The majority of solar cells are designed in a film shape, allowing them to bend but limiting their stretchability.

Recently, fiber-based solar cells have garnered attention due to their potential for enhanced flexibility and adaptability. For example, Chen et al[131] developed a dye-sensitized solar wire by using aligned CNT fiber and TiO_2 nanotubes, achieving an energy conversion efficiency of 4.6%. Similarly, Qiu et al[132] introduced fiber-shaped perovskite solar cells via an electromechanical deposition process, which delivered a higher efficiency of 7.1%, as shown in Figure 7D. However, despite their fiber-based design, the stretchability of these solar cells remains suboptimal due to the reliance on inorganic materials. To address this limitation, Lv et al[133] designed a highly efficient organic solar cell in a fiber shape, offering excellent 1D conformability and weave-ability. Figure 7E displays the fiber being integrated into the fabric and the power of the smartwatch under light. Organic solar cells present significant potential for future wearable applications due to their superior elasticity compared with inorganic materials. Substantial efforts have been made to enhance the energy conversion efficiency of such solar cells. For instance, Zeng et al[134] developed an all-polymer organic solar cell with a large light-receiving angle, achieving an impressive efficiency of 19.06% and demonstrating superior illumination

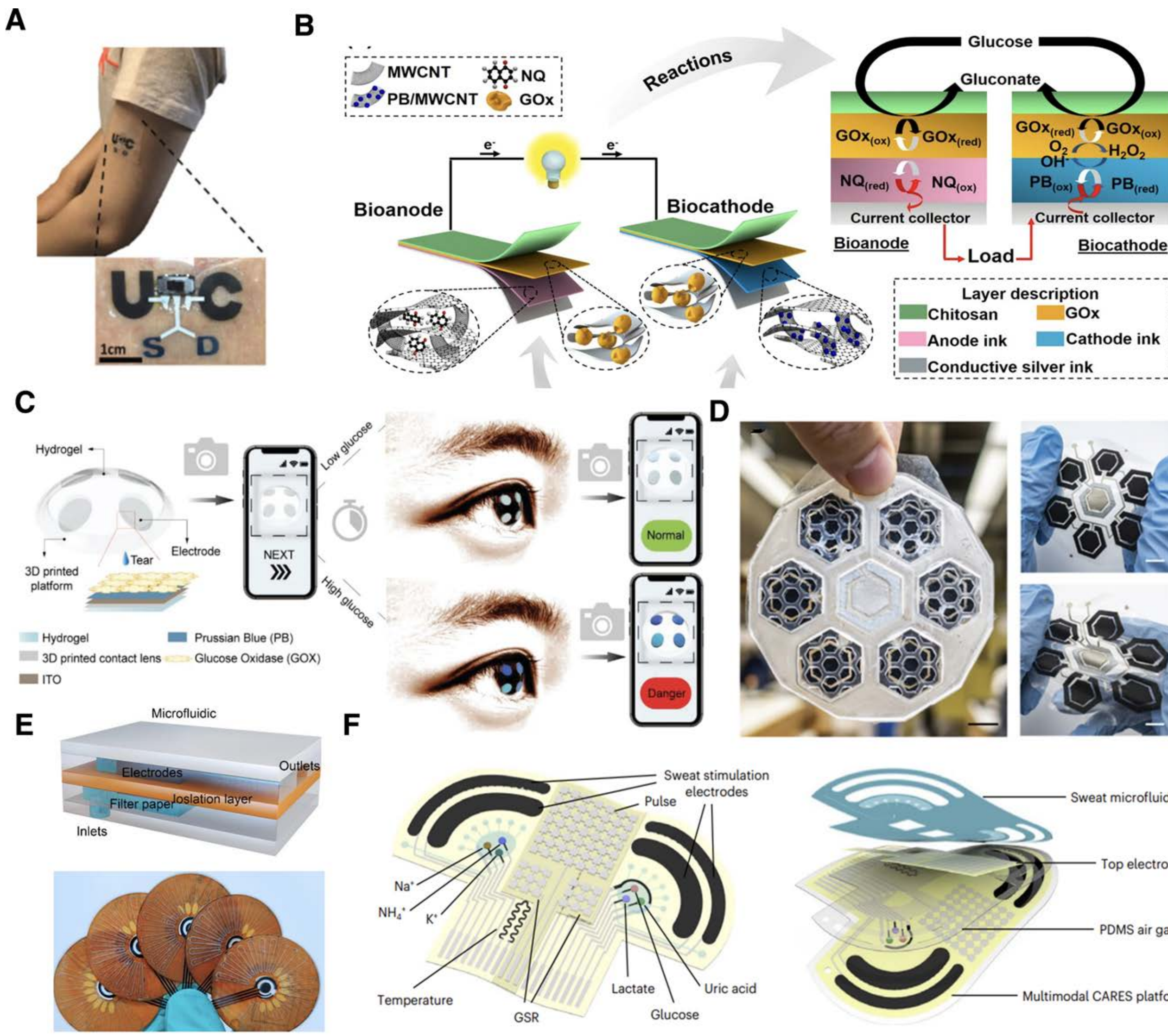

Figure 8. Progress in biofuel cells. (A) Resettable electrochromic biosensor powered by lactate biofuel cells. Adapted with permission from Hartel et al,[142] Copyright © 2022, Elsevier Ltd. (B) Single-enzyme-based biofuel cells based on screen-printable nanocomposite inks. Adapted with permission from Veenuttranon et al,[143] Copyright © 2023, Springer Nature Limited. (C) A smart contact lens based on a biofuel cell system for glucose sensing. Adapted with permission from Li et al,[144] Copyright © 2023, Wiley-VCH GmbH. (D) Sweat-lactate-based biofuel cells with rechargeable Zn–AgCl batteries. Adapted with permission from Yin et al,[140] Copyright © 2022, Wiley-VCH GmbH. (E) Multimodal wearable biochip for monitoring sweat phenylalanine. Adapted with permission from Zhong et al,[145] Copyright © 2024, Springer Nature Limited. (F) Physicochemical-sensing electronic skin for stress monitoring. Adapted with permission from Xu et al,[146] Copyright © 2024, Springer Nature Limited.

stability for up to 1200 hours. Furthermore, Zheng et al[135] reported a tandem organic solar cell with a groundbreaking efficiency of 20.2% as indicated in Figure 7F, marking the first instance of surpassing the 20% efficiency threshold. Continuous advancements in this field have consistently pushed efficiency records higher. In summary, solar cells contribute to sustainable, self-powered systems, reducing reliance on external batteries and improving convenience for athletes.

3.5 Biofuel cells

Recent developments in biofuel cells have emphasized material innovations, structural designs, and wearable applications to address challenges in efficiency, scalability, and integration with real-world systems.[136] Flexibility and wearability are achieved by integrating fiber-based electrochemical sensors into smart textiles through techniques like weaving, embroidery, and knitting, enabling real-time health monitoring.[137] The application of nanomaterials, such as CNTs[136] and graphene,[138] enhances conductivity, surface area, and enzyme-electrode electron transfer efficiency. Lee et al[139] developed stretchable enzymatic biofuel cells based on microfluidic-structured elastomeric PDMS. The wrinkled gold electrodes significantly increased the surface area, enabling high catalyst loading and efficient enzymatic reactions, even under mechanical deformation. This design demonstrated high stretchability and robust power output, making it suitable for energy-harvesting applications in wearable health-monitoring systems. Yin et al[140] combined sweat-lactate-based biofuel cells with rechargeable Zn–AgCl batteries in a wearable e-skin microgrid (Figure 8D). This system efficiently harvested biochemical energy and provided stable power storage, ensuring autonomous operation for extended periods. The integration of biofuel cells with energy storage modules eliminated the need for complex power management systems, enabling continuous operation in wearable devices for sweat sensing and health monitoring. Innovative materials derived from renewable sources are also being explored for biofuel cells. Lou et al[141] synthesized biomass-derived carbon heterostructures through the pyrolysis of lignocellulose, creating nonporous, graphitized carbon materials with enhanced conductivity and environmental adaptability. These materials, designed to support wideband electromagnetic wave absorption, can be adapted to biofuel cell electrodes, providing stable performance under various environmental conditions and expanding their applicability to real-world wearable devices.

For wearable sensing applications, Li et al[144] introduced a smart contact lens that utilized a biofuel cell system for glucose sensing (Figure 8C). The device employed electrochromic Prussian blue electrodes to provide a direct, color-based glucose readout, eliminating the need for external power or wireless communication. This innovative approach demonstrated the feasibility of biofuel cells for autonomous, noninvasive health monitoring. Veenuttranon et al[143] developed screen-printable nanocomposite inks for single-enzyme-based biofuel cells (Figure 8B). By combining glucose oxidase with CNTs and Prussian blue, they achieved a high power density and stable performance under mechanical stress. This system, integrated into wearable biosensors, enabled glucose detection in artificial sweat, highlighting its potential for scalable and flexible health-monitoring applications.

In addition to glucose monitoring, biofuel cells are being adapted for tracking broader metabolic indicators. Hartel et al[142] designed a resettable electrochromic biosensor powered by lactate biofuel cells for continuous sweat-lactate monitoring (Figure 8A). The integration of electrochromic displays with biofuel cells enabled visual feedback without external instruments, improving the usability and practicality of wearable sensors for continuous health monitoring. Zhong et al[145] developed a multimodal wearable biochip for monitoring sweat phenylalanine, which integrated advanced electrochemical electrodes and microfluidic channels (Figure 8E). This biochip correlated sweat biomarkers with blood levels, providing insights into metabolic states during exercise. The system's ability to operate autonomously using biofuel cells underscores the potential of biofuel cells in multisensor wearable platforms for personalized health tracking. Xu et al[146] extended the application of biofuel cells to stress monitoring by creating a physicochemical-sensing electronic skin capable of continuous operation (Figure 8F). This system monitored multiple sweat biomarkers, including glucose and lactate, alongside vital signs such as pulse waveform and skin temperature. The electronic skin demonstrated robust stability over extended periods, leveraging biofuel cells to enable real-time, autonomous health monitoring for stress and metabolic conditions.

3.6 Wearable antennas

Advancements in fabrication techniques for wearable antennas are crucial to address the demands for flexibility, stretchability, miniaturization, and lightweight design. These antennas must conform to the human body, endure mechanical deformations, and maintain stable electrical performance.[50,150] Precise fabrication methods, such as 3D printing and inkjet printing, enable the creation of complex structures with high precision, while layered assembly improves performance in compact designs.[151] Techniques like photolithography and etching ensure fine features for high-frequency applications, and the integration of conductive threads or fabrics into textiles creates stretchable and wearable designs.[152,153] Embedding antennas in elastomers like PDMS enhances durability and stretchability, while liquid metals offer self-healing properties and excellent conductivity.[154,155] These methods collectively ensure that wearable antennas achieve high electromagnetic performance, environmental resistance, and seamless integration with various substrates, enabling applications in healthcare, communication, and beyond. Shao et al[147] introduced a room-temperature direct printing approach using additive-free MXene-based inks (Figure 9A). This method allows high-precision fabrication of wireless electronic components, including antennas, on flexible substrates without the need for postprocessing, achieving superior electrical conductivity and compatibility with diverse surfaces. Li et al[148] leveraged 3D weaving technology to fabricate textile-based antennas embedded with electromagnetic metamaterials (Figure 9B). By embedding conductive yarns into spacer fabrics, this method not only improved mechanical strength but also suppressed surface wave radiation, resulting in a significant gain increase from 5.1 to 9.6 dB. Mirzajani et al[149] employed femtosecond laser ablation to produce compact and flexible NFC antennas, demonstrating precise control over antenna geometry. This process integrates the antennas seamlessly into health-monitoring systems, eliminating the bulk and rigidity of traditional electronic components (Figure 9C). Arulmurugan et al[156] utilized screen-printing techniques to develop a dual-band wearable textile antenna integrated with an electromagnetic bandgap structure. This fabrication approach achieved gains of 6.59 dB and 7.03 dB in the 2.48 GHz and 5.2 GHz bands, respectively, while reducing the specific absorption rate (SAR), ensuring safety and compatibility for wearable applications

Structural design plays a critical role in the development of wearable antennas to ensure optimal performance, durability, and user comfort. The necessity for advanced structural designs stems from the unique requirements of wearable applications. Wearable antennas must conform to the human body's curvature while maintaining efficient electromagnetic performance, even under mechanical deformation such as bending, stretching, or twisting.[157] Miniaturization and lightweight structures are essential for user comfort, while durability is required to withstand environmental conditions like moisture, sweat, and mechanical wear.[152] Additionally, antennas must integrate seamlessly with textiles or flexible substrates without compromising functionality. For instance, Yang et al[158] designed a broadband circularly polarized all-textile antenna, leveraging characteristic mode analysis and flexible felt substrates to achieve high gain and omnidirectional radiation patterns. This antenna was particularly effective for both on- and off-body communication, addressing challenges posed by the dynamic nature of wearable devices. Yu et al[159] presented a dual-band, dual-circularly polarized antenna equipped with an artificial magnetic conductor reflector. This innovative design achieved high gains (11.9 dBic at 3.5 GHz and 10.5 dBic at 5.8 GHz) and minimized SAR, making it highly suitable for 5G and IoT applications. Zhang et al[160] developed a wearable localized surface plasmon antenna that combined compact size and multiband functionality. The design used polyimide as a substrate to ensure flexibility and comfort, while the antenna maintained stable performance even under mechanical deformation. The antenna also demonstrated capabilities in both communication and sweat-sensing applications, showcasing its multifunctionality. Moreover, Zhang et al[161] proposed a wideband circularly polarized antenna with a metasurface plane for biomedical telemetry. This design employed a crossed dipole structure with a metasurface reflector to improve gain and axial ratio bandwidth, ensuring reliable communication with implanted devices while conforming to the human body.

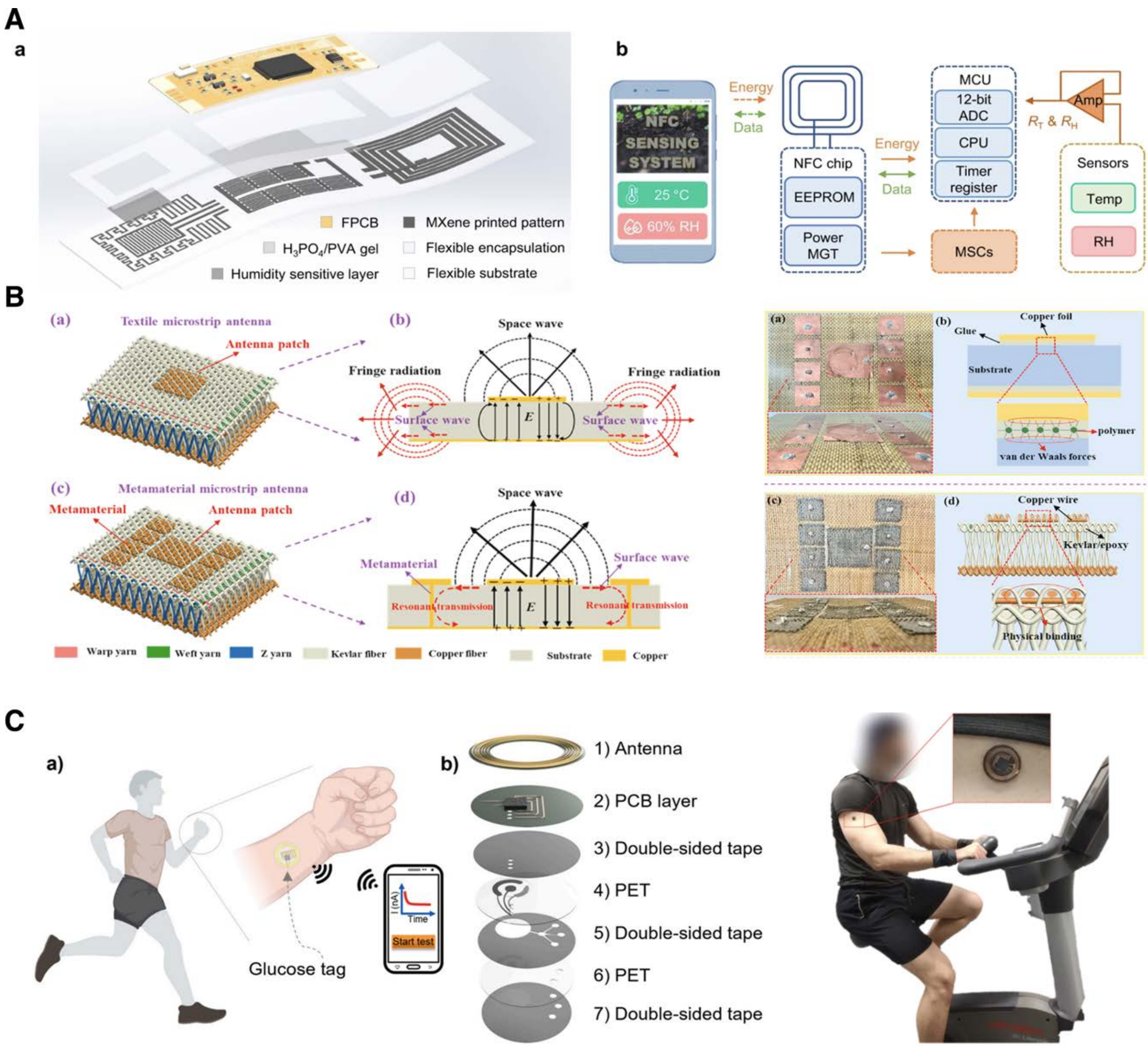

Figure 9. Progress in wearable antenna. (A) Scheme of the all-MXene-printed wearable antenna. Adapted with permission from Shao et al,[147] Copyright © 2022, Springer Nature Limited. (B) Diagram of metamaterial antenna using 3D weaving technology. Adapted with permission from Li et al,[148] Copyright © 2024, Elsevier Ltd. (C) Configuration of a glucose tag for health monitoring. Adapted with permission from Mirzajani et al,[149] Copyright © 2022, Elsevier Ltd.

While wearable antennas do not inherently possess self-powered characteristics, the autonomous operation of the system can be achieved through the effective integration of a rectenna for radio-frequency (RF) energy harvesting. Rectennas combine an antenna with a rectifier for converting electromagnetic energy, typically from RF sources, into direct current power.[162] The main components of a rectenna include the antenna for capturing RF energy, the rectifier for conversion, and often a filter to smooth the resulting DC output. Key challenges in rectenna design involve enhancing efficiency, particularly at low power levels, optimizing the matching between the antenna and rectifier, and ensuring a broad frequency response while minimizing energy losses.[163]

4. AI in sensing systems

4.1 AI model selection in healthcare sensing systems

AI is becoming an essential technology for processing signals collected by sensors. By utilizing AI techniques to extract features and patterns, it identifies valuable information within the signals, transforming them into interpretable semantics or classifications that meet our needs.[164] Compared with traditional signal analysis methods, AI has a lower dependency on the macroscopic interpretability of signals. This allows it to uncover deeper feature correlations, significantly reducing the high standards required for sensor signal patterns.[165] Consequently, this alleviates the design burden on sensors and enhances the accuracy of signal recognition on the data processing side. AI is generally divided into two categories: traditional ML and DL.

4.1.1 Traditional ML algorithm

Traditional ML, known for its high computational efficiency and relatively simple models, has been widely applied in wearable sensor data analysis. Common traditional ML models include support vector machines (SVM),[166] decision trees,[167] random forests,[168] and k-nearest neighbors,[169] which are used for tasks

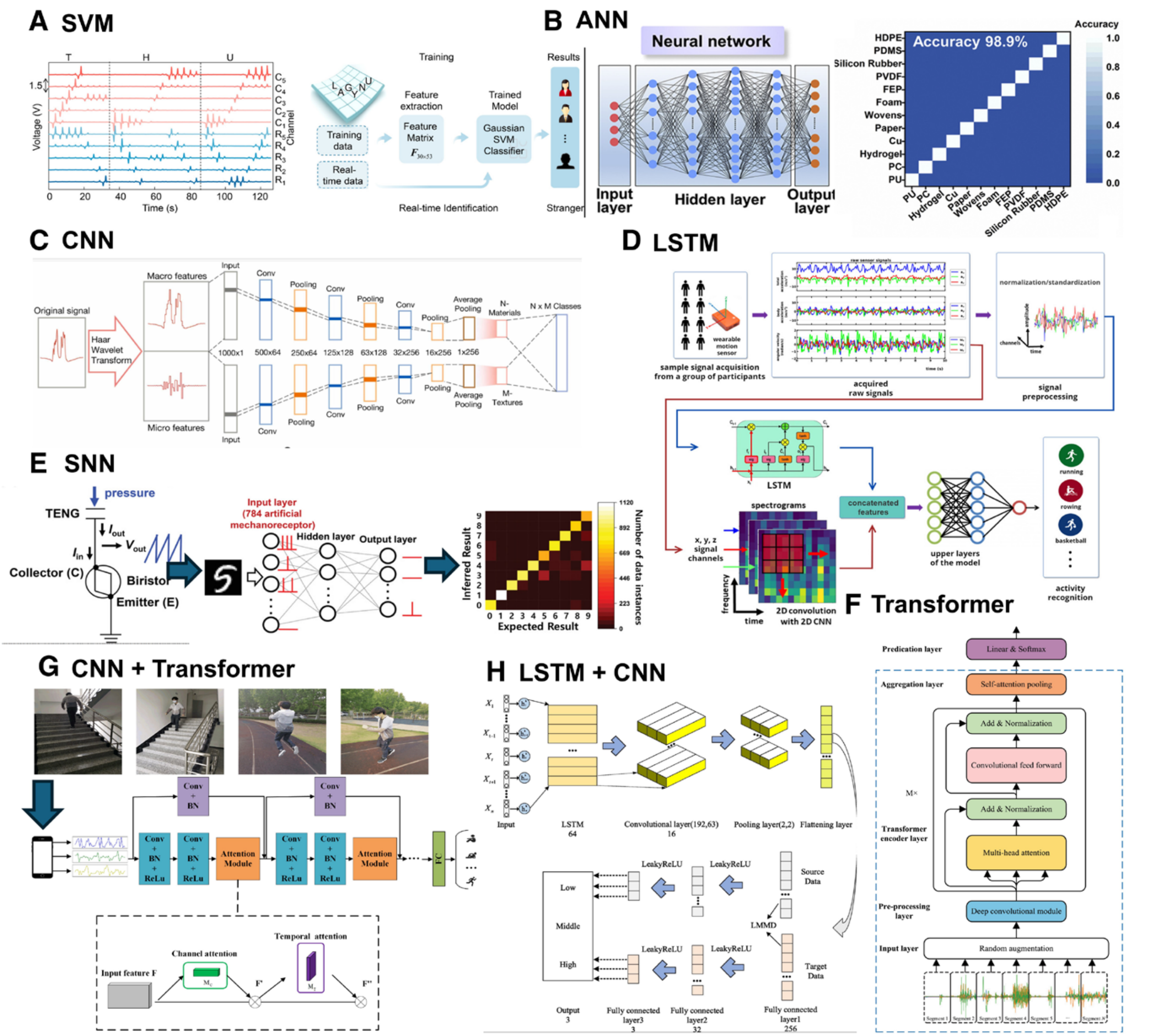

Figure 10. AI techniques in sensing systems. (A) Traditional ML model SVM for user identification. Adapted with permission from Luo et al,[170] Copyright © 2022, American Chemical Society. (B) DL model ANN for material type recognition. Adapted with permission from Wei et al,[173] Copyright © 2022, Cell Press. (C) DL model CNN for object shape recognition. Adapted with permission from Zhang et al,[175] Copyright © 2023, Elsevier Ltd. (D) DL model LSTM for activity type and intensity recognition. Adapted with permission from Koşar et al,[177]; © 2023, Elsevier Ltd. (E) DL model SNN for handwritten digit recognition. Adapted with permission from Han et al,[174] Copyright © 2022, Wiley-VCH GmbH. (F) DL model Transformer for activity recognition. Adapted with permission from Sun et al,[178] Copyright © 2024, Elsevier Ltd. (G) Hybrid DL model CNN + Transformer for multimodal human activity recognition. Adapted with permission from Gao et al,[179] Copyright © 2021, Elsevier Ltd. (H) Hybrid DL model LSTM + CNN for motion part recognition. Adapted with permission from Qiu et al,[180] Copyright © 2024, Elsevier Ltd.

such as classification, regression, and clustering. For example, as shown in Figure 10A, Luo et al reported a bioinspired soft sensor array (BOSSA) and further analyzed it using a data-driven algorithm (multilayer perceptron) to extract higher-level features. SVM was employed for user identification tasks with BOSSA, demonstrating an accuracy of 98.9% in identifying 10 users.[170] Many researchers use *t*-distributed Stochastic Neighbor Embedding, a typical dimensionality reduction algorithm, to process data. It preserves the local and global structures of high-dimensional data (eg, gestures, surface materials, objects, and textures) in a low-dimensional space.[171,172] However, traditional ML is well-suited for signal recognition tasks involving small datasets with clear data features. It is simple, fast, and has low computational costs for training and inference, making it widely applied to feature recognition of signals from wearable sensors. However, traditional ML struggles with scenarios involving large datasets and complex tasks. For example, in Luo et al's BOSSA system,[170] SVM was used for user classification due to the distinct signal feature differences between users in small sample datasets, achieving excellent performance. However, for identifying the placement or extraction of 10 different objects, a DL model, such as an artificial neural network (ANN), was employed for feature extraction. This is because the differences in signals collected for object recognition lack clear macroscopic semantic meaning. DL models are better suited to this scenario due to their ability to extract richer information and achieve higher-level feature representation directly from raw signals.

4.1.2 DL algorithm

Compared with traditional ML, DL models have stronger nonlinear mapping capabilities, more robust performance, and higher accuracy. The most commonly used DL model is the ANN, also known as the multilayer perceptron (MLP), which consists solely of stacked fully connected layers and features a simple structure. As shown in Figure 10B, Wei et al[173] reported a hybrid electronic skin composed of a piezoresistive pressure sensor and a TENG. Enhanced by an improved ANN, the system achieved high-precision sensing with an accuracy of 98.9% for 12 different materials. Moreover, ANNs are also often combined with physical components to form spiking neural network (SNN) models specifically designed for processing spiking signals. As shown in Figure 10E, Han et al designed an SNN model based on a triboelectric nanogenerator. The nanogenerator mimics biological mechanoreceptors to detect pressure and encode spiking signals, serving as input neurons for the SNN. The SNN model was trained using backpropagation to analyze the signals, achieving an accuracy of 85.8% on handwritten digit classification tasks.[174]

ANNs are generally used to handle multi-feature inputs but are not well-suited for processing signal sequences or time series. In contrast, 1D convolutional neural networks (CNNs), with their weight-sharing convolutional units and sliding window operations, are better equipped to extract features from sequential signals. As a result, they are widely applied in recognizing voltage signals captured by wearable sensors. Zhang et al[175] designed a highly sensitive single-electrode TENG and compared the performance of three signal recognition models: SVM, Transformer, and ResNet. The CNN-based ResNet model achieved a recognition accuracy of 98.1% in object shape identification tasks. As shown in Figure 10C, Song et al[176] designed a wireless and fully integrated tactile sensing system, MTSensing, and designed a dual-channel data fusion 1D convolutional model. This model processes decoupled signals from the sensor into macro and micro features to predict the material and texture of contacted objects, achieving accuracies of 99.07% and 99.32%, respectively.

When the signal features from sensors are too long, recurrent neural networks (RNNs) are employed to address the issue of early feature forgetting in long-term sequence processing. The most commonly used units in this context are long short-term memory (LSTM) and gated recurrent unit. As shown in Figure 10D, Koşar and Barshan[177] proposed an LSTM-based hybrid network model to process signals collected by wearable sensors, simultaneously recognizing human activities. The proposed hybrid model exhibits superior performance metrics and acceptable complexity. Additionally, the Transformer model, a mainstream framework in natural language processing, is also widely applied in signal processing, similar to RNNs. As shown in Figure 10F, Sun et al[178] proposed a contrastive self-supervised model based on a deep convolutional transformer to enhance wearable sensors for efficient human activity recognition. The proposed model achieved mean F1 scores of 95.64%, 88.39%, and 98.40% on the UCI-HAR, Skoda, and Mhealth datasets, respectively.

In addition to using a single type of general-purpose neural network model, combining multiple network architectures and designing task-specific hybrid models tailored to the characteristics and working scenarios of wearable sensors can undoubtedly better adapt to tasks and achieve superior recognition performance. As shown in Figure 10G, Gao et al[179] proposed a dual attention method called DanHAR that combines CNNs with transformers, which fuses temporal attention on channel and residual networks to improve the feature representation ability for sensor-based human activity recognition tasks. As shown in Figure 10H, Qiu et al[180] proposed a hybrid network combining LSTM and CNN to optimize wearable sensors. After feature extraction using the hybrid network, a classification model was constructed through a deep subdomain adaptation network algorithm, achieving an average classification accuracy of 91.62% for movements across 8 body parts.

Overall, in the field of AI-assisted self-powered healthcare, traditional ML and DL each have their own characteristics and advantages. Their differences in data processing, model design, and application scenarios mean that a rational selection and integration of these two approaches can not only leverage their respective strengths but also compensate for each other's weaknesses, thereby advancing the intelligent and personalized progress of healthcare management.

Traditional ML has distinct advantages in feature engineering, model interpretability, and low-resource environments. It is well-suited for healthcare monitoring and early-warning scenarios where the data volume is small and real-time performance is required. Traditional ML typically relies on experts to design and extract representative features in advance. For example, when processing medical sensor data, key indicators such as heart rate and blood oxygen saturation might need to be extracted based on experience. Because it depends on pre-extracted features, its model complexity is relatively low, the training speed is faster, and computational resource consumption is minimal, making it easier to debug and interpret. Its excellent interpretability enables researchers and clinical experts to more easily understand the basis for the model's decisions, which helps build trust in medical settings. Therefore, when the data is limited and the structure is clear, the use of carefully designed features can often enhance the model's interpretability and stability.

In contrast, DL excels in precise diagnosis and prediction on large-scale, multimodal data due to its powerful automatic feature learning capability and its ability to capture complex data patterns, although it also faces challenges such as higher computational demands and lower interpretability. Represented by deep neural network models, DL can automatically extract and learn complex features from raw data without requiring extensive manual intervention, making it suitable for processing complex, multimodal data such as medical images, time-series signals, and genomic data. In a big data environment, DL models can efficiently integrate multiple sources of information—such as data from wearable devices, electronic health records, and genomic datasets—through complex network structures. For complex physiological signals (eg, ECG and electroencephalogram [EEG]), DL can capture subtle changes to provide more accurate predictive models for disease warning.

In future practical research, traditional ML and DL are not mutually exclusive but can complement each other:

(1) Hybrid models: Traditional methods can be used for initial feature extraction and selection, followed by DL for refined analysis, thereby improving overall efficiency and accuracy.
(2) Enhanced interpretability: To address the "black box" issue of DL models, current research is attempting to introduce interpretability-enhancing algorithms (such as visualization and attention mechanisms) to improve the transparency of medical decision-making.
(3) Resource allocation: Lightweight traditional models can be deployed on edge devices, while DL is used in the cloud to handle big data, with both working in tandem to construct a comprehensive healthcare management system.

4.2 AI for physiological signal recognition and detection

AI for physiological signal recognition and detection is revolutionizing healthcare by providing high-precision, real-time, and personalized solutions for health monitoring and disease diagnosis.[181] These methods, combined with diverse wearable sensing devices, analyze complex signal patterns from raw signals such as ECGs,[182] EEGs,[183] blood oxygen levels,[182] and EMGs[184] using advanced ML and DL algorithms, enabling rapid and accurate estimation of the test subject's task demand state. In these studies, AI is responsible for identifying the subjects' actions or states based on the signals collected by sensors, thereby providing supplementary information for further healthcare.

AI-assisted sensor-based HMI technology holds tremendous potential in the medical field. Its goal is to enhance diagnostics, treatment, and patient experience through intuitive and efficient interaction, combining human perception with computational and device capabilities. Zhu et al[185] reported an AI-enhanced, wearable, self-powered, and sustainable HMI sensor applied to human finger movements and their virtual activities as shown in Figure 11A. In this study, AI was utilized to classify fast and slow finger movements, demonstrating remarkable visualization capabilities and excelling in clustering, visualization, and handling motion speed disturbances. Zhang et al[186] developed a triboelectric sensor and its array (TSA) that mimics the synaptic structure of neural cells, as shown in Figure 11B. Enhanced by a deep CNN, the system extracts higher-level motion features from electrical signals, enabling a single sensor to identify which body part is producing motion with an accuracy of 98.89%. By combining TSAs with varying numbers of sensors, the system achieves high-precision recognition of motion language, offering significant potential for assisting in the rehabilitation of patients with limb injuries. Li et al[187] proposed a wearable device composed of EMG and strain sensors to address the clinical assessment of muscle strength (MS), as shown in Figure 11C. The device collects surface EMG and mechanical signals from the same location during various muscle activities. They designed a DL model based on temporal convolutional networks and Transformers, which leverages deep feature extraction from temporal signals to achieve accurate grading and prediction of 25 levels of MS. Fang et al[188] proposed a gesture recognition system using a triboelectric intelligent wristband, enhanced by an adaptive accelerated learning (AAL) model, as shown in Figure 11E. The AAL model features a significantly smaller size compared with traditional neural networks while offering superior and faster classification performance. It achieved a recognition accuracy of 97.56% in training tasks with 21 categories and enabled low-latency (<1 second) real-time proprioceptive remote control. Deng et al[189] developed a novel wearable electromechanical coupling sensor using zinc oxide and enhanced it with a 1D CNN for recognizing and classifying different human motions, as shown in Figure 11F. The system achieved 100% recognition accuracy

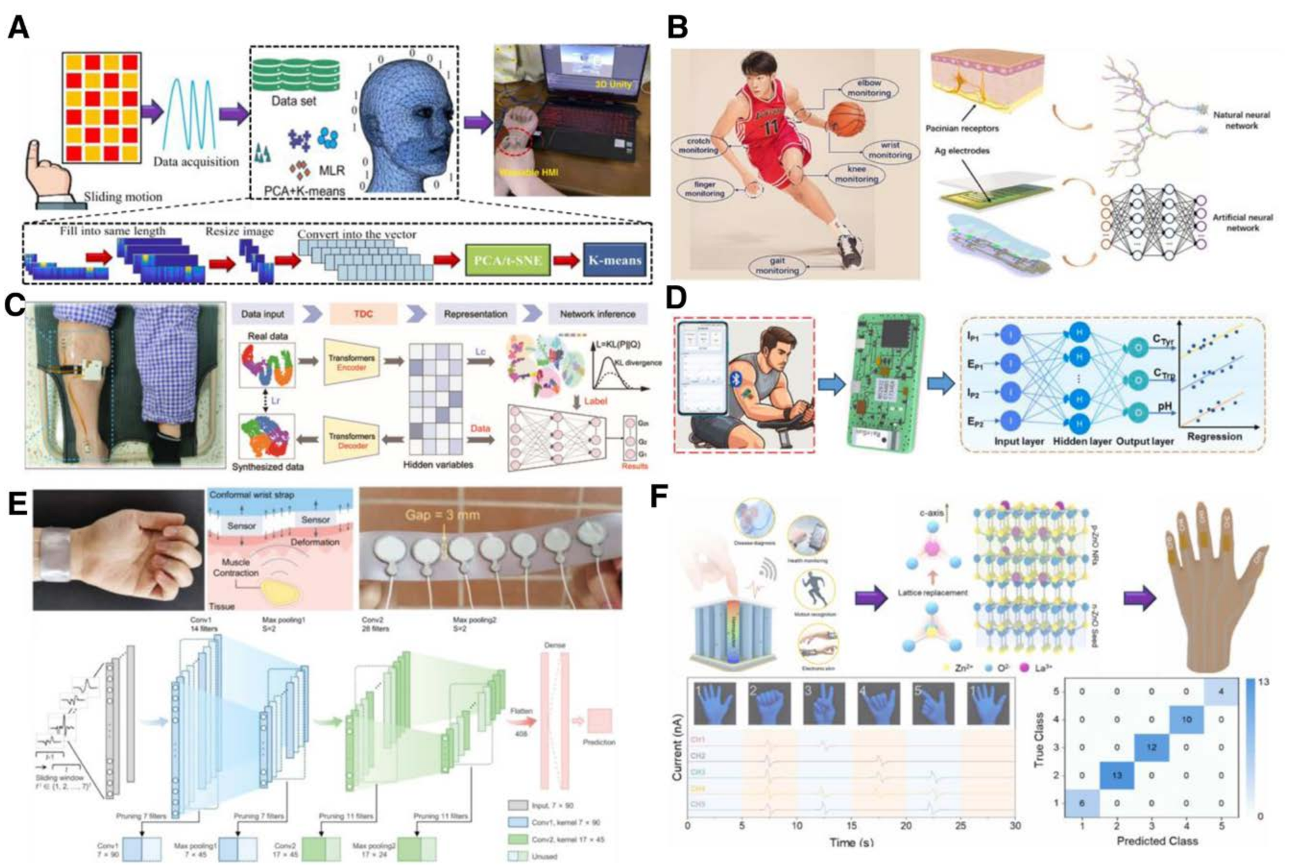

Figure 11. AI-assisted sensing systems for physiological signal recognition and detection. (A) AI-enhanced HMI for human finger movements detection. Adapted with permission from Zhu et al,[185] Copyright © 2022, Elsevier Ltd. (B) AI-enhanced TSA for body part movement recognition. Adapted with permission from Zhang et al,[186] Copyright © 2023, Elsevier Ltd. (C) AI-enhanced EMG sensor for MS assessment. Adapted with permission from Li et al,[187] Copyright © 2024, The American Association for the Advancement of Science. (D) AI-enhanced nonenzymatic sweat sensor for sweat biomarkers monitoring. Adapted with permission from Zhou et al,[190] Copyright © 2024, Elsevier Ltd. (E) AI-enhanced triboelectric intelligent wristband for gesture recognition. Adapted with permission from Fang et al,[188] Copyright © 2023, Wiley-VCH GmbH. (F) AI-enhanced electromechanical coupling sensor using zinc oxide for human motion recognition. Adapted with permission from Deng et al,[189] Copyright © 2024, Elsevier Ltd.

during testing. Additionally, some studies design HMI systems based on bodily fluids. Zhou et al[190] developed a highly selective nonenzymatic sweat sensor as shown in Figure 11D. A designed ANN was applied in these sensors to reliably sense and physiologically monitor sweat biomarkers during the test subject's physical activity. The system enabled the device to generate four interpretable features, which were used to accurately predict the concentrations of tyrosine and tryptophan as well as the pH value of the sweat. Wang et al[191] reported a bioinspired data fusion architecture for wearable e-skin. The sensing component consists of skin-like stretchable strain sensors made from single-walled CNTs. By combining visual data with proprioceptive data from the sensors through a deep ANN, the system achieves human gesture recognition with 100% accuracy. Kim et al[192] reported a novel electronic skin based on substrate-less nanomesh receptors, with the nanomesh made of biocompatible materials that can be directly printed onto human hands. The study integrated an unsupervised meta-learning framework with the sensors and developed a time-correlated contrastive learning algorithm, enabling user-independent, data-efficient recognition of various hand tasks. Moin et al[193] reported a wearable surface electromyography biosensing system based on a conformal electrode array fabricated through screen printing. The system implemented a neuro-inspired hyperdimensional computing algorithm for enhanced real-time gesture classification, as well as model training and updating under variable conditions such as different arm positions and sensor replacements. Experimental results demonstrated a classification accuracy of up to 97.12% for 13 gestures, which remained high at 92.87% when the number of gestures was expanded to 21.

Based on the above review, the advantages of AI-assisted signal recognition can be revealed:

(1) Sensitivity to weak signals: AI, particularly DL models, can automatically extract deep features from complex physiological signals and detect subtle or inconspicuous changes that traditional methods often miss, achieving higher sensitivity.
(2) Suitability for dynamic monitoring: AI methods exhibit high generalization and inference speed, surpassing traditional analytical techniques. They can be deployed on mobile devices to analyze real-time streaming data and provide immediate feedback, making them particularly suitable for applications requiring continuous data collection and analysis.
(3) Multimodal integration capability: AI can integrate signals from various sensors, enabling end-to-end multimodal data analysis and reducing potential errors inherent in single-signal data.

4.3 AI for rehabilitation

AI is playing an increasingly important role in the fields of healthcare and rehabilitation. With its powerful data processing and learning capabilities, it offers revolutionary solutions for disease diagnosis, treatment decision-making, rehabilitation training, and personalized health management, particularly when integrated into health devices.[184] In the development of AI-assisted medical sensing devices, wearable sensors that are remote, lightweight, sensitive, accurate, and real-time provide intelligent diagnostic and therapeutic support to a wide range of populations.[182] In these studies, AI is responsible for directly conducting medical-related evaluations based on the physical signals collected by sensors. Compared with Section 4.2, where the AI technology is more general-purpose, the research in Section 4.3 directly handles end-to-end healthcare tasks.

Fang et al[24] developed a low-cost, lightweight, and mechanically durable textile triboelectric sensor for high-fidelity and continuous pulse waveform monitoring in scenarios involving movement and sweating, as shown in Figure 12A. Enhanced by ANNs, the textile triboelectric sensor can continuously and accurately measure systolic and diastolic blood pressure, while also enabling predictions and cardiovascular health diagnostics. Gao et al[194] developed a wearable sensor integrated with pneumatic actuators and piezoelectric components for in vivo measurement of muscle elasticity, as shown in Figure 12B. A CNN was designed to process the voltage signals collected by the sensor, enabling the assessment of the severity of neuromuscular diseases. Li et al[195] designed a portable sensor combining triboelectric and electromagnetic principles for highly sensitive detection and rapid recognition of human motion, as shown in Figure 12C. An ANN was developed for gesture recognition and limb disability detection, addressing the need for generalization across multiple scenarios. Bao et al[196] reported a sparse sensor network equipped with a soft wireless IMU device for the early clinical assessment of infant brain development, as shown in Figure 12D. A miniature ML algorithm was integrated into the sensing system to automatically identify at-risk infants based on general movements, achieving an accuracy of up to 99.9%. Shin et al[197] reported an AI-enhanced wireless multimodal wearable system capable of automatically and accurately conducting clinical assessments of swallowing behavior and diagnosing silent aspiration in patients with dysphagia as shown in Figure 12E. In this study, a deep neural network combining 1D convolution layers and LSTM units was developed, achieving an 89.47% classification accuracy for swallowing patterns. Guo et al[198] presented a flexible self-powered piezoelectric sensor patch (SPP) using a PVDF fibrous membrane as the functional layer as shown in Figure 12F. The sensor employed an LSTM-based network model as AI assistance to process data collected from the SPP for wrist joint motion recognition, aiding in flexibility assessment. The motion recognition tests achieved an accuracy of 92.6%. Yang et al[199] proposed a dual-response piezoelectric pressure sensor for monitoring athletes' rehabilitation training, as shown in Figure 12G. Assisted by an ML algorithm guiding rehabilitation actions, the system, based on ANNs and random forests, achieved 100% recognition of rehabilitation maneuvers. Zeng et al[200] developed wearable sensors based on epidermal electronic systems for monitoring mental fatigue in scenarios such as driving and healthcare. The study employed AI algorithms to determine mental fatigue levels, achieving up to 89% prediction accuracy using a decision tree algorithm based on 6 different physiological features. Researchers have also designed AI-based high-sensitivity biosensors for early detection of diseases such as cancer and diabetes. Kim et al[201] addressed the challenge of high false-positive rates in early prostate cancer screening by designing a learning-capable urinary multibiomarker biosensor. The sensor utilized two common ML algorithms to analyze the correlation between clinical conditions and urinary multibiomarker sensor signals, identifying the

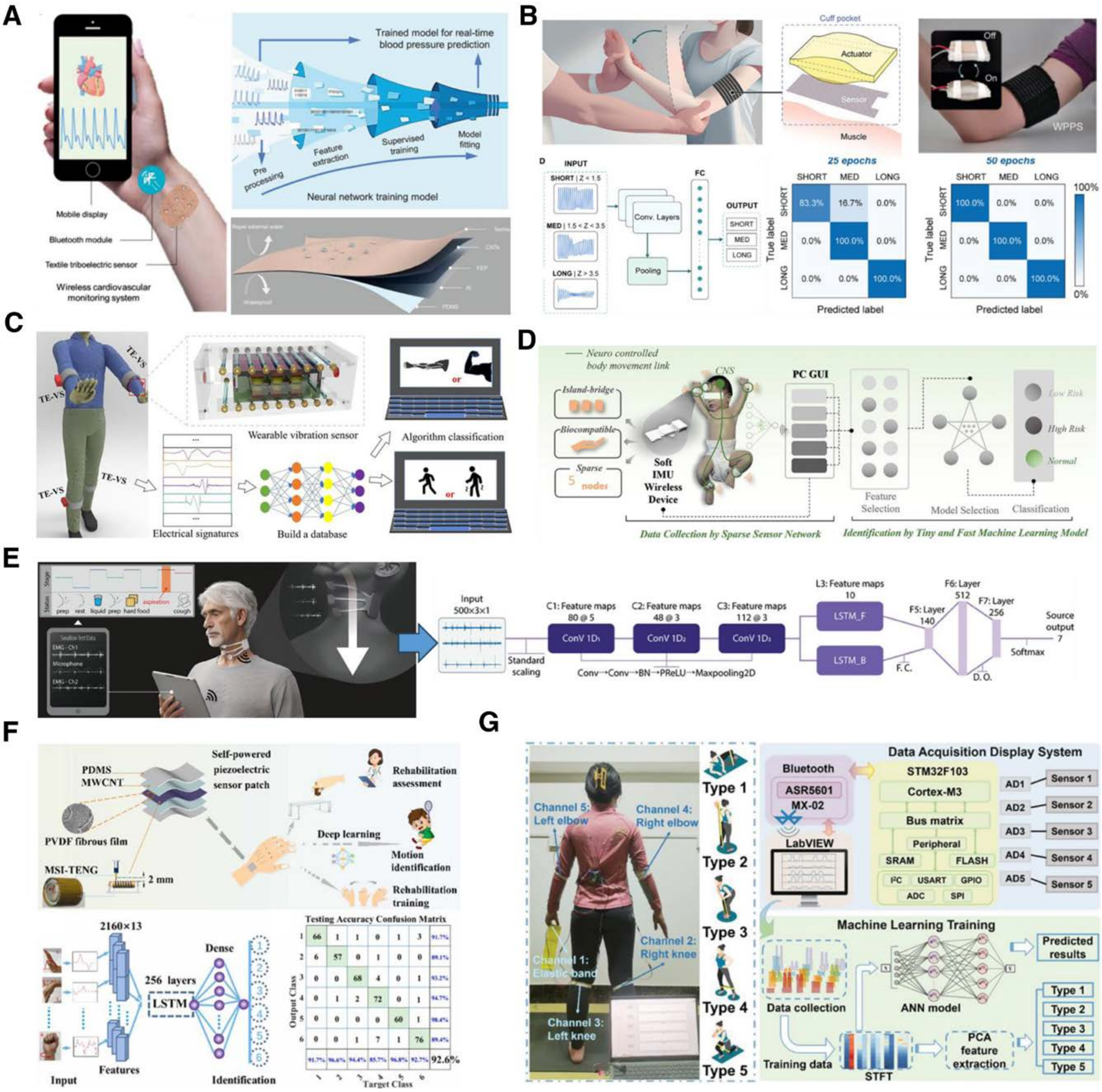

Figure 12. AI-assisted sensing systems for rehabilitation. (A) AI-assisted textile triboelectric sensor for continuous pulse waveform monitoring. Adapted with permission from Fang et al,[24] Copyright © 2021, Wiley-VCH GmbH. (B) AI-assisted wearable sensor for in vivo measurement of muscle elasticity. Adapted with permission from Gao et al,[194] Copyright © 2024, Cell Press. (C) AI-assisted portable sensor for recognition of human motion. Adapted with permission from Li et al,[195] Copyright © 2023, Elsevier Ltd. (D) AI-assisted sparse sensor network for the early clinical assessment of infant brain development. Adapted with permission from Bao et al,[196] Copyright © 2024, Wiley-VCH GmbH. (E) AI-enhanced wireless multimodal wearable system for conducting clinical assessments of swallowing behavior. Adapted with permission from Shin et al,[197] Copyright © 2024, Wiley-VCH GmbH. (F) AI-assisted self-powered piezoelectric sensor for wrist joint motion recognition. Adapted with permission from Guo et al,[198] Copyright © 2024, Elsevier Ltd. (G) AI-assisted piezoelectric pressure sensor for monitoring athletes' rehabilitation training. Adapted with permission from Yang et al,[199] Copyright © 2024, Wiley-VCH GmbH.

optimal combination of biomarkers. In screening 76 urine samples, the sensor achieved an accuracy exceeding 99%. Li et al[202] addressed the challenges of large-scale screening and early identification of COVID-19 infections during the pandemic by developing a rapid, ultrasensitive, multifunctional plasmonic biosensor based on surface-enhanced infrared absorption for on-site COVID-19 diagnosis. In this study, a genetic algorithm-based intelligent program was employed to automate the design and rapidly optimize the sensing device, thereby enhancing sensing performance. As a result, the sensor achieved ultrahigh sensitivity (1.66%/nm), a wide detection range, and adaptability to diverse measurement environments (gas/liquid) for quantitative COVID-19 detection.

The review highlights the advantages of AI-assisted rehabilitation:

(1) Precise rehabilitation assessment and prediction: AI, combined with sensor technology, can monitor patients' motion

states, physiological signals, and rehabilitation progress in real time. Through deep data mining of collected signals, AI can capture subtle motion changes, significantly improving assessment accuracy.

(2) Applicability and generalization: AI excels at learning pattern characteristics across different patients, enabling sensors to generalize effectively for various patient types. Similarly, this feature can be utilized in reverse to achieve patient-specific customization, tailoring sensor designs to meet the needs of individual patients.

5. Conclusion and outlook

In summary, the advancement of AI-assisted self-powered sensors represents a pivotal development in the healthcare sector, offering groundbreaking capabilities for continuous, real-time monitoring and personalized health management. This review highlighted the significant progress made in materials, structural designs, manufacturing methods, and AI integration for wearable self-powered sensors. However, several universal challenges remain, including biocompatibility, durability, stability, perceptual sensitivity, and system autonomy. Improvements in the following areas, as illustrated in Figure 13, could help address these issues.

5.1 Materials exploration

While significant advancements have been made, there remains a need for new materials that offer improved flexibility, durability, and biocompatibility. Achieving high electrical performance in wearable applications while ensuring environmental sustainability is a critical challenge.

5.2 Manufacturing innovation

Scalable and efficient fabrication methods, such as additive manufacturing and electrospinning, require further refinement to support the production of complex and miniaturized sensor designs. Integrating these methods into large-scale production processes without compromising performance remains a key issue.

5.3 Structure optimization

Designing and optimizing bionic structures, hybrid sensing configurations, and advanced architectures to enhance sensitivity and adaptability is an ongoing challenge. Developing structures that can reliably capture weak physiological signals under dynamic conditions is particularly critical.

5.4 Deep AI combination

Although AI has been successfully applied to sensing system operation and data postprocessing, its integration into the design process of self-powered sensors is still in its early stages. Realizing AI-driven optimization for customized sensor designs for healthcare applications are areas of potential growth. In addition, AI-driven adaptive sensing systems are pursued to enhance system autonomy.

5.5 System integration

System integration has the potential to significantly enhance the versatility and practicality of sensing systems. For instance, multifunctional sensor systems represent a pivotal development direction for the future, enabling the simultaneous monitoring of multiple physical signals. Furthermore, the integration of

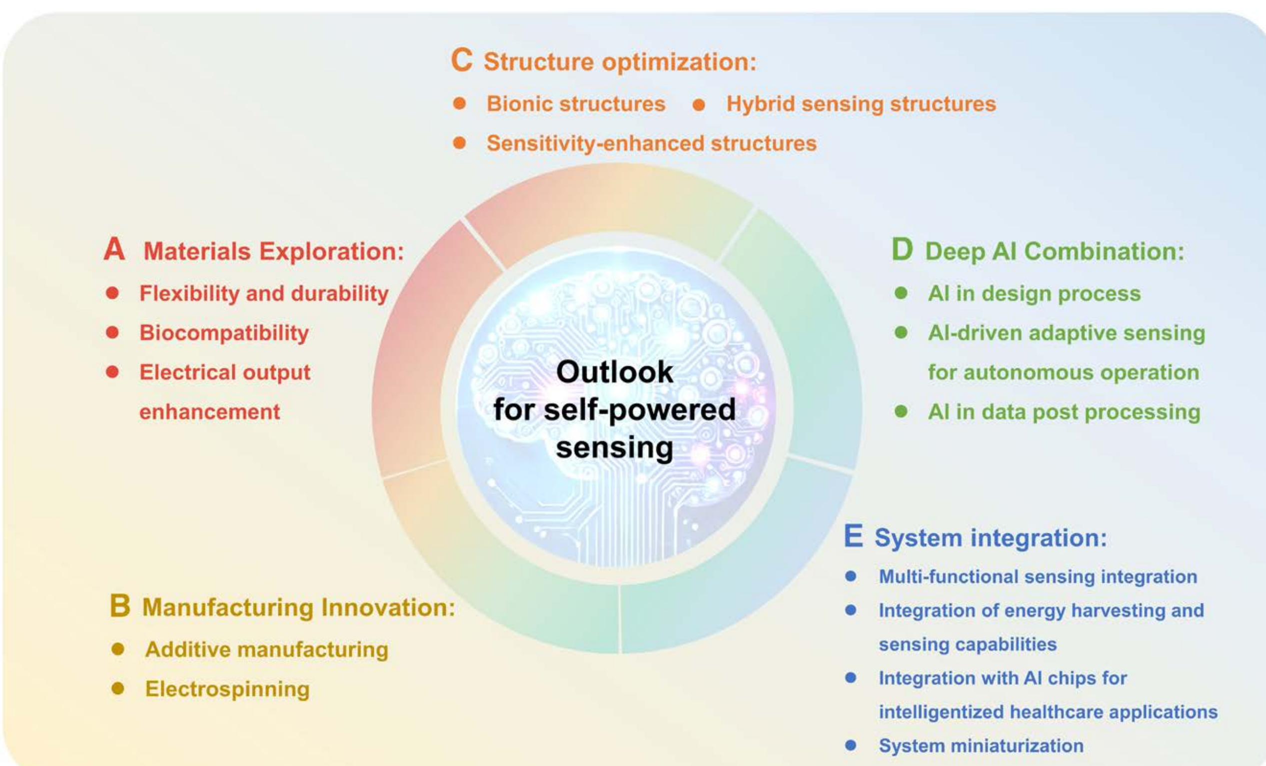

Figure 13. Outlook of self-powered sensing for healthcare applications.

energy-harvesting and sensing functionalities can effectively improve system autonomy, paving the way for fully battery-free designs. Additionally, incorporating AI chips into these systems is a promising avenue for enabling more intelligent and advanced healthcare applications. Moreover, the miniaturization of the integrated system is essential to reduce interference with normal physiological activities.

Future efforts should focus on addressing these challenges through interdisciplinary collaborations across materials science, engineering, and AI. By tackling these obstacles, self-powered sensors can fully realize their potential to transform healthcare, providing intelligent, real-time solutions for medical diagnostics, disease prevention, and rehabilitation.

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Conflicts of interests

The authors declare that they have no conflicts of interest.

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