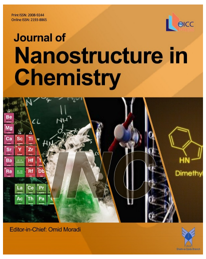

Volume 15, Issue 1, 152504 (1-23)

Journal of Nanostructure in Chemistry (JNSC)

https://doi.org/10.57647/jnsc.2025.1501.04

Progress and Applications of Nanotechnology-Based Wearable Sensors in Human Motion and Posture Detection

Hezhou Li[1], Dan Wang[2,*]

[1]*School of Physical Education and Health, Wenzhou University, Wenzhou, Zhejiang, China.*
[2]*Institute of Physical Education, Hubei University of Science and Technology, Xianning, Hubei, China.*

[*]**Corresponding authors:** wangdan@hbust.edu.cn

Review Paper

Received:
8 January 2025

Revised:
30 January 2025

Accepted:
26 February 2025

Published online:
28 February 2025

Abstract:

The advancement of nanotechnology has revolutionized the development of wearable sensors, offering enhanced sensitivity, flexibility, and real-time performance in human motion and posture detection. This review explores the integration of advanced nanomaterials, including graphene, carbon nanotubes, and metal nanowires, which facilitate the creation of highly conformal and biocompatible sensors. Recent progress in self-powered sensing technologies, such as triboelectric and piezoelectric nanogenerators, has enabled continuous monitoring without the need for external power sources. Moreover, innovations in fabrication techniques, including 3D printing, inkjet deposition, and laser scribing, have improved the scalability and cost-effectiveness of wearable sensor production. The convergence of multimodal sensing approaches-combining inertial sensors, electromyography (EMG), and brain-computer interfaces (BCI)-with artificial intelligence (AI)-based algorithms has further enhanced motion recognition accuracy and adaptive system responses. This review highlights the broad spectrum of applications, ranging from healthcare and rehabilitation to sports performance and industrial safety, while discussing current challenges related to sensor durability, environmental interference, and data processing. Future advancements in material science, sensor fusion, and energy harvesting hold immense potential for developing next-generation wearable sensors capable of seamlessly integrating into everyday life.

Keywords: Energy harvesting; Artificial intelligence; Fabrication techniques; Sensor fusion; Motion recognition

Cite this article: Li, H., Wang, D. Progress and Applications of Nanotechnology-Based Wearable Sensors in Human Motion and Posture Detection. *J Nanostruct Chem* **15**(1), 1-23 (2025).

1. Introduction

The advancement of technology over recent decades has ignited an unprecedented interest in real-time monitoring of human motion and posture. The increasing demand for accurate, continuous, and non-invasive monitoring solutions arises from the diverse applications in healthcare, sports performance, industrial safety, and rehabilitation engineering. Traditional motion tracking systems-such as the Vicon optical motion capture system and Xsens IMU-based suits-have played a significant role in biomechanical analysis and clinical gait assessment. However, these systems exhibit critical limitations. For instance, optical systems like Vicon require multiple high-speed cameras and reflective markers, demanding controlled lab environments and exhibiting susceptibility to occlusion and marker misplacement, with setup times often exceeding 30 minutes and cost upwards of \$100,000 [1]. IMU-based systems, such as Xsens MVN, offer greater portability but remain limited by cumulative drift (e.g., $3-5°$ per minute) and high power consumption ($>$ 100 mW per node) during prolonged use [2, 3]. Moreover, both approaches struggle to conform to complex body geometries, reducing their wearability and comfort for real-time, everyday monitoring. For instance, optical motion capture systems typically require controlled environments and exhibit positional accuracy limited to $1-2$ mm, but are prone to occlusion and require expensive, non-portable setups [1]. Similarly, conventional IMU-based systems often exhibit drift errors of $3-5°$ per minute in orientation tracking without calibration [3], while their power consumption can exceed 100 mW per node, limiting usability in long-term or mobile applications [2]. These drawbacks significantly constrain their applicability in wearable, real-time monitoring scenarios. In contrast, the rapid evolution of nanotechnology-based wearable sensors-particularly those that are flexible, stretchable, and self-powered-offers promising solutions to overcome these challenges [4]. Recent research shows that by integrating advanced nanomaterials with innovative sensor designs, it is possible to create systems that not only mimic the sensitivity and dexterity of human skin but also provide multifunctional capabilities that are critical for modern human-machine interfaces [5, 6]. This paradigm shift has been further accelerated by the incorporation of artificial intelligence (AI) into sensor data analysis, which now enhances the reliability, speed, and adaptability of system responses to human movement [7].

One of the primary motivations behind the exploration of nanotechnology-based wearable sensors is the need for reliable, real-time monitoring systems that can be seamlessly integrated into daily life. In healthcare, accurate monitoring of human motion and posture is crucial for early diagnosis, rehabilitation assessment, prosthetic control, and long-term disease management [8, 9]. For instance, patients recovering from stroke or orthopedic surgeries require continuous feedback on their movement patterns to ensure proper alignment and to avoid further injury [10]. Similarly, in sports and fitness, real-time motion detection not only aids in performance optimization but also plays a preventive role by reducing the risk of injuries due to erroneous techniques or excessive loads [11]. Furthermore, in industrial settings, continuous monitoring of worker postures helps in mitigating ergonomic risks and reducing accident rates by enabling immediate corrective actions [12]. Nevertheless, conventional sensor systems are often limited by their rigid structures and high power consumption, which restrict their usability in dynamic environments or on complex anatomical surfaces [13, 14]. In this context, nanotechnology emerges as a powerful tool, enabling the fabrication of sensors that are not only conformal and lightweight but also capable of self-powering through integration of energy-harvesting mechanisms such as triboelectric and piezoelectric nanogenerators [15, 16]. Furthermore, the efficiency of these systems is greatly enhanced when coupled with innovative data processing mechanisms based on AI algorithms, which facilitate rapid interpretation of complex motion signals [7]. This confluence of material science, nanotechnology, and intelligent algorithms provides the cornerstone for next-generation wearable sensor platforms. Moreover, there is a growing trend towards personalized medicine and individualized health monitoring. As populations age and chronic diseases become more prevalent, the ability to continuously monitor motion and posture in a non-invasive manner is critical for timely interventions and for tailoring rehabilitation protocols to individual needs [17]. Such capabilities enable early detection of adverse conditions through subtle deviations in normal movement patterns, which could be indicative of neurological or musculoskeletal disorders.

The evolution of wearable sensor technologies can be traced back to early attempts at integrating sensors into fabrics and external accessories. Initial systems were predominantly based on bulkier electronics that required rigid enclosures and external power supplies. As research progressed, flexible electronics began to emerge, introducing thin-film configurations and lightweight materials that significantly enhanced user comfort and sensor responsiveness [5]. The advent of nanomaterials, such as carbon nanotubes, graphene, and metal nanowires, further revolutionized the field by enabling sensors that are not only highly flexible and stretchable, but also capable of capturing dynamic mechanical deformations at extremely high resolutions [18]. In recent years, nanogenerator-based self-powered sensors have emerged as a particularly promising class of devices. These sensors harvest biomechanical energy from human motion, thereby eliminating the need for external batteries and substantially reducing overall system complexity [6, 19]. Additionally, researchers have successfully demonstrated advanced sensor arrays utilizing flexible substrates such as polydimethylsiloxane (PDMS) to capture spatial pressure distributions across multiple body regions, thereby improving the resolution and accuracy of human motion detection [20]. Early prototypes in this arena, such as wearable devices based on piezoelectric fiber composites, laid the groundwork for present-day innovations by demonstrating the feasibility of integrating energy-harvesting functionalities within wearable formats [21]. In parallel, the incorporation of machine learning and deep neural networks into sensor systems has enabled real-time data processing and improved interpretation of multi-modal signals [22]. Moreover, with the rapid progress in fabrication techniques such as inkjet printing and roll-to-roll processing, researchers have been able to manufacture sensors on a large scale while maintaining low cost and high performance [15]. This scalability is critical as it paves the way for ubiquitous deployment of wearable sensors in various consumer and clinical applications. The evolution from rigid, bulky devices to seamless, skin-like sensor arrays marks one of the most significant shifts in wearable technology, demonstrating the transformative impact of nanotechnology in this domain.

Accurate human motion and posture detection are of paramount importance across a spectrum of applications. In the medical field, wearable sensors facilitate continuous monitoring of patient movement, thereby enabling early detection of abnormalities that could indicate the onset or progression of disease. For example, sophisticated sensor systems can monitor gait dynamics in stroke survivors or quantify balance control in elderly patients, thereby informing personalized rehabilitation protocols [10]. In the realm of prosthetics and assistive robotics, real-time detection of motion intentions and posture adjustments can be leveraged to create adaptive control systems that respond intuitively to user needs [16]. Additionally, in industrial environments where worker safety is a constant concern, wearable sensors are deployed to monitor posture, detect falls, and prevent musculoskeletal injuries, thereby enhancing workplace safety and efficiency [12]. Furthermore, advances in motion detection technology have spurred progress in sporting applications, where precise monitoring of joint angles and body kinetics has become instrumental in optimizing athletic performance and reducing injury risks [11]. In parallel, the development of machine learning algorithms has improved the identification and classification of complex movement patterns, facilitating accurate detection of abnormal behaviors such as falls or atypical gait cycles [23]. Additionally, non-contact sensing methods based on radio-frequency (RF) signals and 3D imaging technologies have broadened the avenues for unobtrusive posture detection, particularly in scenarios where wearable devices may not be practical [24]. The significance of human motion detection is further underscored by its role in emerging fields such as human-robot collaboration, where the ability to predict and adapt to human motion patterns is essential for safe and efficient integration of robots into everyday environments [25]. In addition, wearable sensors integrated into smart textiles not only provide health monitoring but also enable unobtrusive surveillance of daily activities, thereby contributing to the broader framework of smart cities and connected environments [26]. Such interdisciplinary applications magnify the impact of sensor technology and underscore the need for continued innovation in this space.

This review aims to provide a comprehensive overview of the current progress in nanotechnology-based wearable sensors for the detection of human motion and posture (Fig. 1). Following this introduction, section 2 discusses the advances in nanomaterials, focusing on carbon-based, metallic, and polymeric nanostructures, and their associated fabrication techniques. Section 3 presents the core sensor technologies, including inertial measurement units (IMUs), EMG, brain–computer interfaces (BCIs), and emerging nanotechnology-based sensor modalities. Section 4 explores multimodal sensing strategies and sensor fusion frameworks, with a particular emphasis on deep learning and real-time motion intention prediction. Finally, we identify prevailing challenges and limitations in section 5, before concluding with insights into future research directions. By organizing the review along these axes, we aim to highlight both the breadth and depth of current progress in wearable sensor technologies. We intend to examine the evolution of sensor platforms-from early rigid devices to modern flexible and self-powered systems-and highlight the critical role nanomaterials play in enhancing both performance and user comfort [5]. In particular, we discuss how innovations in material synthesis, sensor design, and system integration have led to versatile devices that are able to monitor complex biological signals with high spatial-temporal resolution. Furthermore, the incorporation of AI-enabled algorithms for data processing and pattern recognition is reviewed as a vital component for translating raw sensor data into clinically and industrially actionable information [7]. Additionally, we explore the interdisciplinary integration of nanogenerator technologies for self-powered sensing and the use of flexible substrates-techniques that are instrumental in creating next-generation wearable devices [6, 17]. We also evaluate recent advances in energy harvesting, such as triboelectric nanogenerators, which have enabled wearable devices that can operate continuously in a self-sustained manner [19]. In terms of system functionality, the review will assess the integration of multi-modal sensing-including pressure, strain, and inertial signals-with advanced algorithms that enable accurate quantification of human motion and posture [20]. The scope of this review is broad and encompasses materials design, fabrication techniques, sensor performance, energy harvesting, and data analytics. In doing so, it provides a multi-faceted outlook on both the achievements and challenges of current nanotechnology-based wearable sensors. We also discuss future research directions and prospective applications, highlighting areas such as remote healthcare monitoring, sports analytics, and human–robot collaboration [25–27]. Finally, the review identifies current technical challenges, such as sensor stability, long-term durability, interference from environmental factors, and the complex

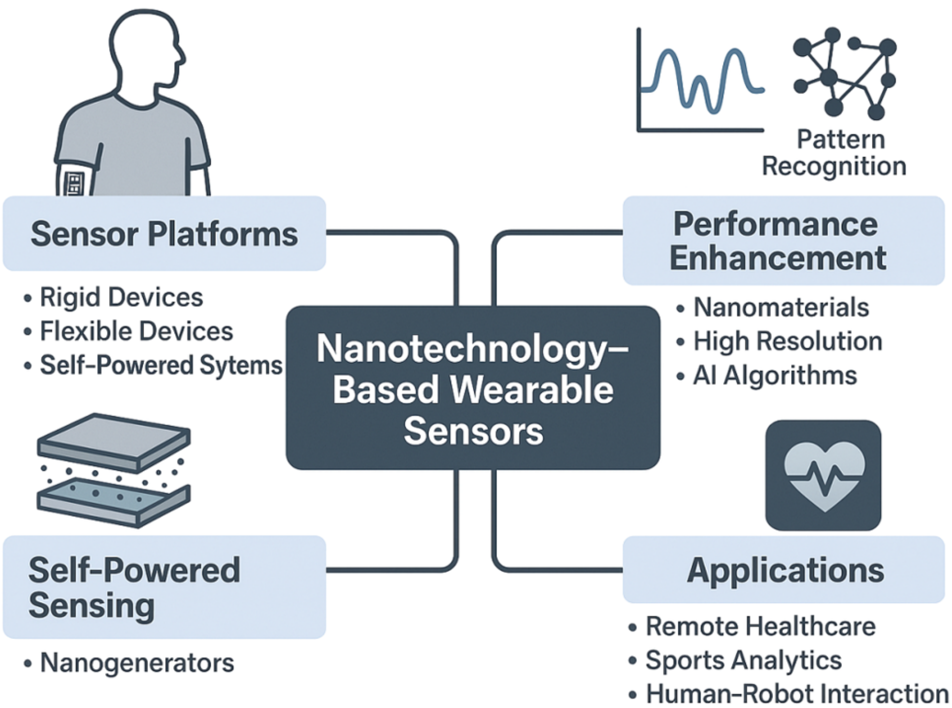

Figure 1. Overview of the current progress in nanotechnology-based wearable sensors for human motion and posture detection.

integration of multi-modal data, all of which are critical to achieving reliable real-world applications.

2. Advances in nanotechnology for wearable sensors

The emergence of wearable sensors has transformed healthcare monitoring, rehabilitation, and sports performance by enabling continuous measurement of physiological parameters and human movements. Early wearable devices were bulky and exhibited limited sensitivity; however, the integration of nanotechnology into sensor design has led to breakthroughs in miniaturization, flexibility, and real-time performance. Recent studies have demonstrated the potential of employing nanomaterials to achieve enhanced sensitivity in strain and pressure sensors, which are key for accurate human motion and posture detection [5, 28]. Furthermore, the growing demand for personalized healthcare and continuous monitoring has spurred research into lightweight, low-power, and biocompatible sensor platforms [29].

2.1 Nanomaterials for sensor development

Nanomaterials have become the cornerstone for advancing wearable sensor performance due to their unique electrical, mechanical, and chemical properties. In this section, we elaborate on the primary classes of nanomaterials that have been integrated into sensor architectures. Figure 2 shows the overview of nanomaterials used in wearable sensors.
Carbon-based nanomaterials, such as graphene, graphene oxide (GO), reduced graphene oxide (rGO), and carbon nanotubes (CNTs), have received considerable attention due to their exceptional conductivity, high specific surface area, and mechanical robustness. For instance, a wearable strain sensor based on rGO-coated fabric demonstrated a gauge factor (GF) of ~ 35 and excellent cycling durability over 10,000 cycles, suitable for elbow joint monitoring [30]. Similarly, CNT-based strain sensors have been used in smart gloves for sign language translation, leveraging their high GF (~ 200) and stretchability ($> 100\%$) [31]. Graphene and its derivatives provide an ultrathin, flexible, and transparent platform for sensor fabrication. Detailed investigations have shown that the incorporation of graphene-related materials leads to improved electron transfer and signal resolution in strain sensors [32, 33]. In addition, CNTs exhibit excellent conductivity and flexibility, making them ideal for the creation of robust, deformable electrodes in wearable applications. Reports indicate that CNT-based strain sensors can achieve a gauge factor of $100-200$, a strain range up to 150%, and rapid response times below 100 ms, which are essential for capturing dynamic human motion [34].
Metal nanoparticles and nanowires, particularly those composed of gold and silver, are widely used to enhance the signal transduction and sensitivity of wearable sensors. Gold nanoparticles offer high chemical stability and biocompatibility, while silver nanowires are renowned for their remarkable electrical conductivity and inherent flexibility. Recent work on Ni-Co metal-organic framework (MOF) nanosheets coated on flexible substrates demonstrated that

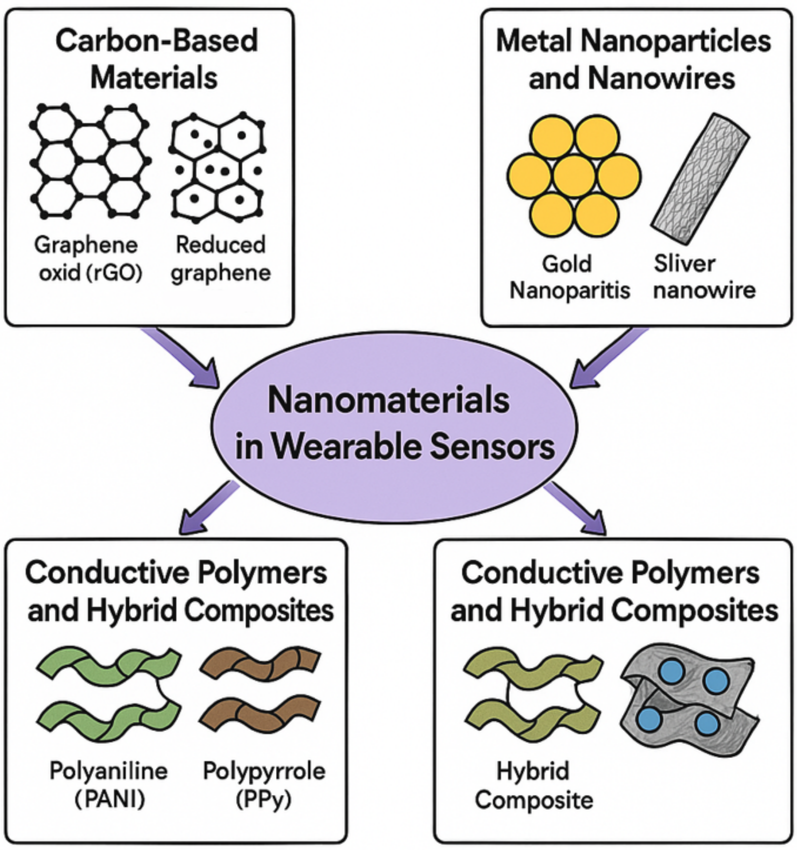

Figure 2. Overview of nanomaterials used in wearable sensors.

such nanomaterials can produce highly sensitive electrochemical sensors for glucose detection, a feature that is directly translatable to motion sensing applications that require precise signal readout [35]. For example, silver nanowire (AgNW)-embedded PDMS films have been used in epidermal pressure sensors with sensitivities up to 1.2 k/Pa and fast response times of < 20 ms, enabling fingertip and gait detection [36]. While AgNWs exhibit superior conductivity and flexibility, they may suffer from long-term oxidation in humid conditions, a limitation not typically observed in more chemically stable materials like graphene. Conductive polymers such as polyaniline (PANI) and polypyrrole (PPy) have been integrated into wearable sensor platforms due to their excellent intrinsic conductivity and biocompatibility. Hybrid composites that combine CNTs with metal oxides or conductive polymers provide synergistic properties that enhance sensor performance. For example, the formation of hybrid nanocomposites has been shown to improve the stretchability and sensitivity of flexible electrodes used in electromechanical sensors [37, 38]. A PANI/CNT hybrid-based textile sensor demonstrated good sensitivity and mechanical stability under repeated bending, making it suitable for integration into sportswear and rehabilitation garments [39]. However, conductive polymers generally exhibit lower intrinsic conductivity than metallic nanostructures and may degrade under extreme pH or thermal conditions, making encapsulation essential for durability.

Among nanomaterials surveyed, graphene and silver nanowires offer superior conductivity, but CNTs provide better stretchability, and conductive polymers ensure improved biocompatibility, making material selection application-dependent.

2.2 Key properties for wearable sensor applications

For wearable sensors to be effective in real-world human motion and posture detection, they must exhibit several key properties. These include mechanical flexibility, biocompatibility, high sensitivity and selectivity, and low power consumption with energy autonomy (figure 3).

Flexibility and stretchability are essential for wearable sensors as they must conform to the complex contours of the human body without compromising performance. Flexible substrates, such as ultrathin polymers and bioinspired materials, enable intimate contact with the skin and ensure stable signal acquisition even during dynamic movements. Research in flexible and stretchable devices has shown significant improvements in sensor durability and performance under mechanical deformation [28, 40, 41].

For wearable devices that maintain prolonged contact with human skin, biocompatibility is a non-negotiable feature. The materials selected must not cause irritation or adverse reactions during long-term use. Advances in nanomaterial synthesis have led to biocompatible surfaces that minimize inflammatory responses and ensure that sensors can be integrated into fabrics or directly on the skin with minimal discomfort [7, 29].

High sensitivity is crucial in wearable sensors designed to detect subtle changes in human motion and posture. For example, strain sensors based on graphene and CNTs have reported gauge factors ranging from 35 to over 1000, with strain detection ranges exceeding 100% in some stretchable configurations [42, 43]. Additionally, pressure sensors incorporating silver nanowire networks have demonstrated pressure sensitivities up to 0.84 k/Pa in the low-pressure regime ($0 - 2$ kPa), making them suitable for detecting fine movements such as finger bending or facial muscle twitches. Nanomaterial-based sensors have demonstrated the ability to detect minute deformations through significant changes in electrical resistance or capacitance, enabling them to accurately capture even low-amplitude movements. Innovations such as bioinspired optical waveguide sensors have further advanced the fine spatial resolution necessary for precise motion tracking [35, 44].

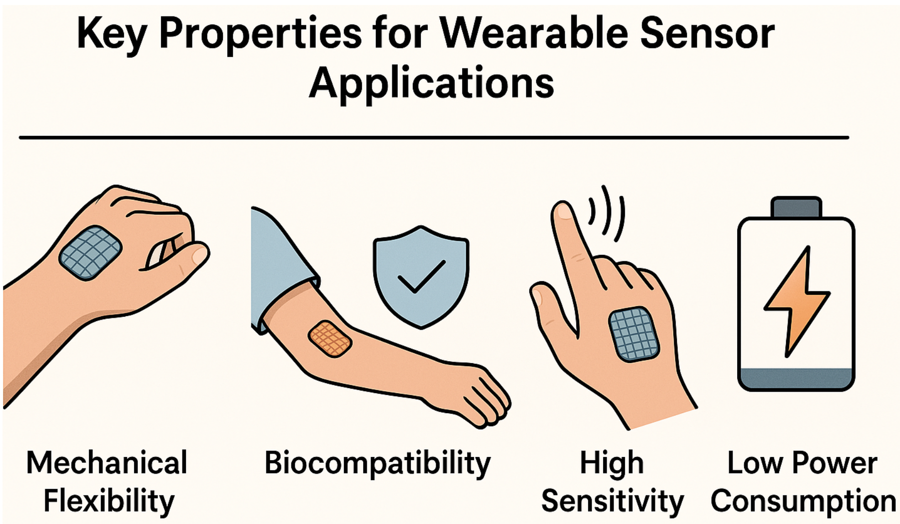

Figure 3. Key properties for wearable sensor applications, highlights four essential characteristics: (1) Mechanical Flexibility – enabling sensors to conform to complex body contours, (2) Biocompatibility – ensuring safe, prolonged contact with human skin, (3) High Sensitivity – detecting subtle changes in motion and posture with high precision, and (4) Low Power Consumption – allowing for energy-efficient, long-term operation through self-powered systems.

Low power consumption is critical in wearable sensor systems to facilitate long-term, battery-free operation. Recent research has focused on integrating self-powered systems, such as piezoelectric nanogenerators and triboelectric devices, with wearable sensors to harness ambient energy from motion and environmental stimuli. These energy harvesting strategies not only reduce the reliance on bulky batteries but also allow for continuous monitoring in remote areas [6, 7, 45, 46].

2.3 Fabrication techniques and integration with wearables

The fabrication of nanotechnology-based wearable sensors for human motion and posture detection relies on a variety of advanced manufacturing techniques. These techniques are not only pivotal in ensuring high precision and reproducibility but also enable the scalable production of sensors that can be integrated onto flexible and conformable substrates. As shown in figure 4, we discuss in detail three prominent fabrication approaches: 3D printing and inkjet printing, laser scribing combined with chemical vapor deposition (CVD), and transfer printing for epidermal sensors. While advanced fabrication techniques like 3D printing, inkjet deposition, laser scribing, CVD, and transfer printing each offer unique advantages in terms of resolution, scalability, and material compatibility, integrating components fabricated using disparate methods presents several technical challenges. For instance, interfacing a CVD-grown graphene layer-typically fabricated at high temperatures and requiring inert or vacuum environments-with an inkjet-printed conductive polymer electrode can result in poor adhesion and interfacial resistance due to differences in surface energy and substrate compatibility. Furthermore, dimensional mismatch (e.g., thickness and roughness) between layers produced by subtractive (e.g., laser scribing) and additive (e.g., inkjet printing) techniques may lead to mechanical delamination under bending or strain. These challenges are compounded in wearable applications, where repeated mechanical deformation demands robust interfacial adhesion and uniform electrical conductivity. To mitigate such issues, strategies such as plasma or UV-ozone treatment to enhance interfacial wettability, use of adhesive interlayers (e.g., PEDOT:PSS or silane coupling agents), and temperature-controlled sequential processing have been explored [42, 52, 53]. Moreover, hybrid fabrication workflows that combine low-temperature inkjet printing with room-temperature transfer printing have been proposed to preserve the integrity of delicate nanostructures while enabling seamless multilayer integration. Addressing these integration challenges is essential for developing reliable, multifunctional wearable sensors with heterogeneous architectures.

2.3.1 3D printing and inkjet printing

Additive manufacturing, especially 3D printing, has revolutionized the production of wearable sensor components by permitting layer-by-layer fabrication with complex geometries. This method is particularly attractive for wearable sensors because it allows for rapid prototyping and cost-effective customization, which is critical when tailoring devices for personalized applications. Polymer systems designed for additive manufacturing facilitate the integration of flexible electronics with robust mechanical properties [6, 54]. The use of inkjet printing further refines this process by enabling the deposition of functional materials with high spatial resolution. Inkjet printing can deposit conductive, piezoelectric, or piezoresistive inks in precise patterns, which is critical for establishing the fine features required in sensor arrays. Systematic comparative studies have highlighted the merits of inkjet-based techniques in terms of line resolution, material efficiency, and compatibility with flexible substrates [55, 56].

A significant advantage of 3D printing lies in its capability to integrate multiple material types within a single device. For instance, the concurrent printing of flexible substrates and conductive traces enables not only the fabrication of robust sensor bodies but also the minimization of interfacial resistance between different device regions (figure 5)

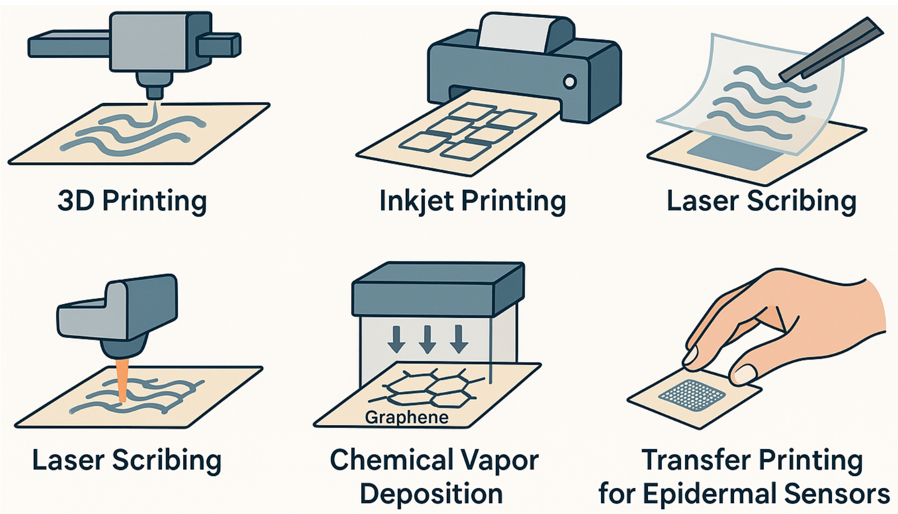

Figure 4. Overview of fabrication techniques for nanomaterial-based sensors, highlighting key methods such as 3D printing, inkjet printing, laser scribing, CVD, and transfer printing for epidermal sensors.

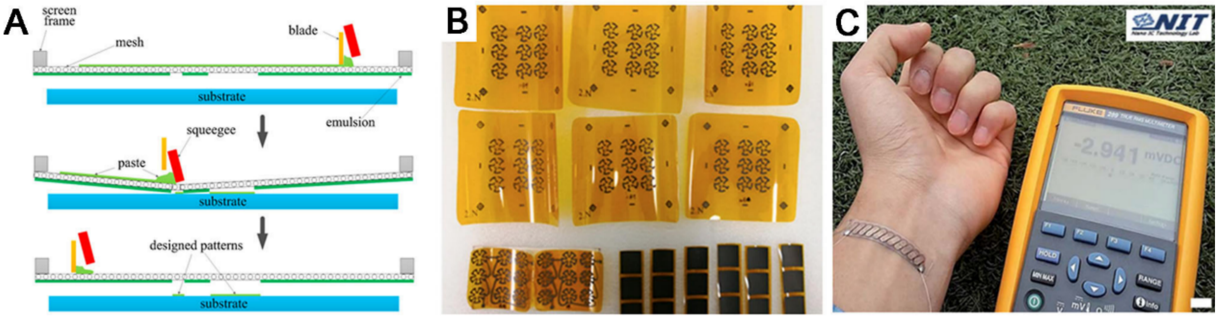

Figure 5. (A) Schematic diagram showing the pattern deposition by screen printing. Reproduced with permission [47]; (B) Screen-printed radial structured TEG with n-type $Bi_2Te_{2.7}Se_{0.3}$ and p-type $Bi_{0.5}Sb_{1.5}Te_3$ on polyimide substrates. Reproduced with permission [48]; (C) Screen-printed TEG on flexible glass fabric substrate and the voltage generated using human body heat [49].

[57, 58]. This integrated approach has been foundational in supporting the development of wearable devices, as it can produce sensors with high sensitivity, mechanical robustness, and low power consumption. The scalability of these techniques further ensures that sensor devices are produced in volume with repeatable quality [59, 60].

Furthermore, recent advances in material formulations have broadened the range of printable inks to include nanocomposites and conductive polymers. The integration of nanoparticles and carbon-based materials via inkjet deposition enhances the electrical conductivity and mechanical flexibility of sensors while ensuring that the active layers are sufficiently thin for wearable applications [61, 62]. The combination of 3D printing and inkjet printing is thus emerging as a versatile platform for creating highly integrated wearable sensor systems that require precise material deposition alongside the scalability necessary for commercial manufacturing.

2.3.2 Laser scribing and chemical vapor deposition (CVD)

While additive manufacturing methods such as 3D printing excel in producing complex three-dimensional geometries, other fabrication techniques are required to achieve the nanometer-scale precision that many wearable sensors demand. Laser scribing, for example, is a high-precision process that uses controlled laser beams to ablate or pattern thin film conductive layers, thereby creating microstructures with sub-micrometer accuracy. This technique is invaluable when fabricating electrodes and interconnects within sensor devices, as it allows the definition of intricate patterns necessary for high sensor resolution [63, 64]. Figure 6 shows several examples of using laser scribing for wearable sensor fabrication.

Complementing laser scribing, CVD is a process widely used to deposit thin films of diverse materials such as metals, semiconductors, and two-dimensional materials (e.g., graphene) with exceptional purity and uniformity. The precise control afforded by CVD makes it ideally suited for producing nanostructured layers that can serve as the active sensing components or protective coatings in wearable devices [32, 33]. Recent research efforts have integrated laser scribing and CVD to produce high-performance sensors by first patterning a substrate with laser ablation and then depositing functional materials via CVD. This combination allows the fabrication of sensor arrays with both spatial precision and excellent material properties, which is crucial for the detection of subtle changes in human motion and posture [65, 66].

The evolution of these techniques has been driven by the need for miniaturization and enhanced performance in wearable electronics. As nanostructured materials become more critical for sensor performance, precise control over film morphology and thickness via CVD, combined with the localized material removal offered by laser scribing, provides an optimal pathway toward creating sensors with the

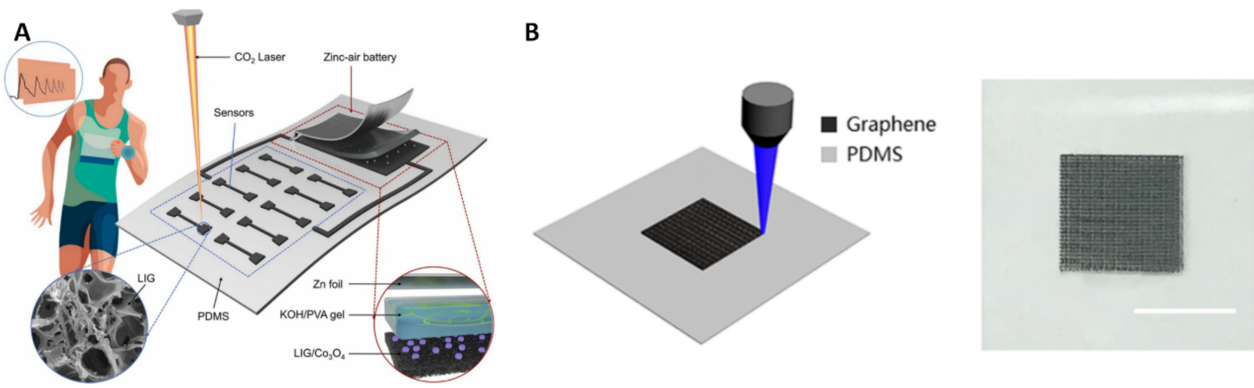

Figure 6. (A) Configuration of the flexible all-in-one sensing system that integrates a sensitive strain sensor and a rechargeable zinc-air battery. Reproduced with permission [50]; (B) Graphene produced by direct laser scribing PDMS films. Reproduced with permission [51].

required sensitivity and durability [67, 68].

2.3.3 Transfer printing for epidermal sensors

The successful integration of wearable sensors onto the skin requires fabrication methods that are compatible with ultrathin, flexible, and stretchable substrates. Transfer printing has emerged as a leading approach for achieving this integration. In transfer printing, functional sensor elements are fabricated on a donor substrate and subsequently transferred to a target substrate, typically an elastomer or a bioinspired adhesive material. This method allows the retention of high electronic performance while providing mechanical compliance that matches the softness of human skin [69, 70]. Table 1 summarizes the comparison of transfer printing techniques classified according to the design of structural architectures and adhesive materials. Notably, transfer printing methods can be combined with other fabrication techniques such as laser scribing or inkjet printing to pre-pattern functional layers before transfer. For example, ultrathin graphene or carbon nanotube networks-fabricated by CVD or inkjet deposition-can be transferred onto a flexible polymer substrate to form highly conductive electrodes for epidermal sensors [7, 71]. In addition to producing electrodes, transfer printing is critical for the integration of other functional sensor components such as microfluidic channels, strain gauges, and temperature sensors. By enabling the direct transfer of pre-fabricated sensor layers onto the skin, this approach minimizes interfacial issues and enhances the mechanical stability of the device during repetitive deformation due to body movement [72, 73].
The versatility of transfer printing is further enhanced by its compatibility with roll-to-roll processing, which allows for the continuous fabrication of ultrathin sensor arrays. This scalability is essential for mass production and commercialization of wearable sensor systems designed for continuous human motion and posture monitoring [6, 58]. Moreover, transfer printing enables the integration of heterogeneous materials and devices, which is a critical advantage when combining rigid semiconductor elements with soft polymeric substrates. Such heterogeneous integration extends the functionality of wearable sensors, allowing them to monitor a range of physiological parameters, from mechanical deformation to bioelectrical signals, while maintaining user comfort and device reliability [62, 74].

3. Wearable sensors for human motion and posture detection

The recent advances in nanotechnology and microelectromechanical systems (MEMS) have led to the development of innovative wearable sensors that are capable of accurately detecting human motion and posture. In this chapter, we discuss four major classes of wearable sensors used in such applications: inertial sensors (IMU/MIMU) for motion tracking, EMG-based sensors for muscle activity monitoring, brain-computer interface (BCI) systems for motion intention prediction, and emerging nanotechnology-based sensor technologies. Each section provides a detailed overview of the working principles, sensor fusion algorithms, and typical application scenarios-ranging from industrial worker monitoring to clinical rehabilitation—thereby illustrating the critical role of these sensors in advancing personalized healthcare and human-machine interaction.

3.1 Inertial sensors and motion tracking (IMU/MIMU)

3.1.1 Working principle and sensing mechanism

Inertial sensors, which typically include accelerometers, gyroscopes, and magnetometers, form the backbone of many wearable motion tracking systems. Accelerometers are designed to measure linear acceleration, providing critical information regarding the translational movement of body segments. In contrast, gyroscopes detect angular velocity, offering insight into rotational movement and orientation changes. Magnetometers complement these sensors by detecting the Earth's magnetic field to provide an absolute reference for heading, thereby mitigating the drift errors commonly observed with gyroscopes. The synergistic integration of these sensing modalities in an IMU ensures

Table 1. Comparison of transfer printing techniques classified according to the design of structural architectures and adhesive materials.

Category	Representative Scheme	Materials and Structures	Advantages	Challenges
Ultrathin Membranes of Electronics	Thin, flexible membrane devices with serpentine or mesh circuits	Polyimide or PET substrates with serpentine-patterned copper or gold traces	- High flexibility and stretchability - Minimal mechanical strain - Good electrical performance	- Prone to damage under repeated deformation - Weak adhesion without bonding agents
In-Plane Structures of Electronics	Flexible circuit patterns embedded within substrate plane	Silver nanowires, CNT networks, or printed conductive inks on TPU or PDMS	- Good conformability to curved surfaces - Durable under strain - Suitable for epidermal electronics	- Complex fabrication process - Limited integration with rigid components
Soft Adhesive Layers	Sensors attached via biocompatible, soft adhesives	PDMS elastomers, hydrogel films, ionic adhesive layers	- Strong skin adhesion - Comfortable for long-term use - Simple application	- Irreversible adhesion - Affected by moisture or sweat - Potential for skin irritation
Bioinspired Structured Adhesives	Adhesion inspired by biological structures (e.g., gecko, octopus)	Micro-pillar arrays, mushroom-cap patterns, suction cups, interlocking microneedles	- Reusable and reversible - Conformal to irregular surfaces - Switchable adhesion possible	- Fabrication complexity - Limited scalability - Lower mechanical robustness in long-term use

a robust measurement of dynamic movements with high temporal resolution and low latency.
At the core of these devices lies the ability to convert mechanical deformation into electrical signals via piezoelectric or capacitive effects, which in turn are processed by on-board microprocessors for real-time interpretation. Over the past two decades, miniaturization and advancements in MEMS technologies have enabled the fabrication of multi-axis inertial sensors with enhanced sensitivity, reduced power consumption, and improved reliability. These features are vital for applications that range from capturing subtle changes in postural sway to monitoring rapid, high-intensity movements in sports or industrial settings [75–77]. In addition, the physical principles underlying signal transduction in such sensors have been further enhanced by the integration of nanomaterials, which improve sensitivity through their high surface-to-volume ratios and customizable electronic properties.
The mechanism of inertial sensors is not only limited to static posture estimation but is also capable of detecting dynamic variances in human movement. This dynamic capability is particularly important in the context of digital health, where continuous monitoring of limb kinetics is required for applications such as fall detection, rehabilitation robotics, and athletic performance optimization. Furthermore, with the advent of smart textiles and flexible substrates, it is now possible to integrate these sensors seamlessly into clothing, thereby enabling unobtrusive and long-term monitoring during daily activities.

3.1.2 Sensor fusion techniques for improved accuracy

Despite the intrinsic advantages of individual inertial sensors, the limitations of each-especially in terms of noise, bias drift, and sensitivity to external disturbances-necessitate the adoption of sensor fusion techniques. The Kalman filter is one of the most widely used algorithms in this context. It operates through recursive Bayesian estimation by combining measurements from accelerometers, gyroscopes, and magnetometers with a dynamic motion model to reduce sensor drift and noise. Complementary filters, which blend high-pass filtered gyroscope data with low-pass filtered accelerometer data, are commonly used for orientation tracking due to their simplicity and real-time performance. More advanced fusion techniques incorporate adaptive filters or use physics-informed neural networks to improve robustness under dynamic conditions [80–82]. By optimally estimating the system state, the Kalman filter significantly reduces errors that result from the independent limitations of accelerometers, gyroscopes, or magnetometers. Complementary filtering provides an alternative method, combining high-pass filtered gyroscope data (which retains information on rapid movement changes) with low-pass filtered accelerometer data (which is more stable but sensitive to slow changes and drift). Advanced implementations have incorporated unscented variants and adaptive techniques that adjust noise covariance parameters in real time [83–86].
In addition to these classical methods, recent approaches have employed hybrid techniques that combine the strengths of model-based methods with data-driven artificial intelligence algorithms. For instance, physics-aware motion optimizers that incorporate deep neural network outputs offer notable improvements in temporal stability and physical correctness of motion reconstruction. Such methods not only enhance accuracy over long-duration measurements but also allow for real-time estimation in dynamic environments-an essential requirement for industrial and sports applications. Many studies have demonstrated the successful integration of sensor fusion methodologies in real-life applications. In settings where inaccurate posture estimation may have serious safety implications, such as industrial work or emergency response training, the refined state estimates achieved by these algorithms become indispensable [87]. Furthermore, the combination of multiple sensing modalities minimizes the impact of sudden disturbances or occlusion issues that might otherwise compromise single-sensor measurements, thus making the technology more robust and reliable for continuous monitoring.

3.1.3 Applications in industrial and clinical settings

The extensive application potential of inertial sensor-based systems is underscored by their deployment in both industrial and clinical domains. In industrial scenarios, wearable IMU-based devices are used to monitor the movement patterns and postural dynamics of workers to detect early signs of fatigue and overexertion, thereby reducing the risk of musculoskeletal injuries. Real-time feedback from these sensors facilitates the design of ergonomic interventions and informs training programs that aim to improve worker safety [88–91]. In clinical settings, these devices are used for gait and posture analysis in rehabilitation, enabling precise monitoring of patient progress and aiding in the evaluation of therapeutic interventions. For example, sensor-based assessments of joint kinematics have provided clinicians with quantitative data to customize rehabilitation protocols for patients recovering from strokes or musculoskeletal injuries. Moreover, the integration of inertial sensors into wearable platforms has enabled the development of home-based rehabilitation systems. By combining inertial data with computer vision techniques, these systems can provide objective, real-time feedback on the quality of movement during unsupervised exercise sessions [92]. This paradigm shift has not only increased the accessibility of rehabilitative care but also promoted long-term adherence through engaging, data-driven feedback systems.

3.2 Electromyography (EMG)-based wearable sensors

3.2.1 sEMG and intramuscular EMG technologies

EMG provides a window into the electrical activity of muscles, serving as an invaluable tool for understanding neuromuscular function. There are two primary approaches: surface EMG (sEMG), which is noninvasive and widely used for monitoring overall muscle activation patterns, and intramuscular EMG, which involves the insertion of fine-wire electrodes directly into the muscle tissue to capture localized signals with higher specificity. sEMG techniques have gained popularity in wearable sensor applications due to their ease of integration, lower cost, and greater user comfort. These sensors are readily incorporated into smart textiles or adhesive patches and are especially useful in scenarios where continuous monitoring is required. However, it is important to acknowledge that sEMG, by nature of its surface placement and signal averaging over larger muscle areas, has limited spatial resolution. This poses challenges in accurately isolating activity from small, adjacent muscles-such as those involved in fine motor control of the hand or face-where signal crosstalk and attenuation may obscure true muscle-specific activation patterns [93]. As a result, sEMG may be less effective for applications requiring high selectivity, such as dexterous prosthetic control or neuromuscular diagnostics in dense muscle regions. In such cases, intramuscular EMG offers superior specificity, albeit at the expense of invasiveness and integration complexity. Recent studies have attempted to overcome these limitations in sEMG by using high-density EMG (HD-sEMG) arrays and advanced signal decomposition techniques to extract motor unit activity with finer resolution [95]. These advances help bridge the gap between non-invasive sEMG and the detailed insights typically offered by intramuscular recordings, but further improvements are still required for real-time, wearable implementations.

Recent advances in sensor design have led to the development of hybrid systems that combine sEMG with other sensing modalities, such as IMUs, to provide a richer and more contextual understanding of both muscle activation and limb movement dynamics. This integrated approach is essential for decoding complex motor tasks and for tailoring rehabilitation programs in patients with neuromuscular disorders. Figure 7 shows examples of nanomaterials enhanced EMG.

3.2.2 Signal acquisition and processing

The acquisition of EMG signals poses several technical challenges due to the inherent noise and variability in bioelectrical signals. To ensure high-quality signal capture, several preprocessing steps are typically employed, including filtering, amplification, and normalization. Feature extraction methods-such as time-domain statistics, frequency-domain analyses, and wavelet transforms-are then used to distill the essential characteristics of the muscle activity. Advanced machine learning and deep learning algorithms have also been applied to classify different muscle activation patterns and to detect subtle changes associated with fatigue or abnormal motor function. For instance, recent studies have demonstrated the use of neural network-based regression models to predict joint angles and EMG signals from integrated sensor data, with estimation errors of less than 2% and temporal resolution under 50 ms, which meets the requirements for real-time motion feedback in rehabilitation and prosthetic control [96]. Such algorithms not only enhance the reliability of EMG-based monitoring systems but also enable real-time implementation in wearable devices, thereby enhancing the responsiveness of prosthetic control systems and rehabilitation aids.

Moreover, the integration of advanced signal processing methodologies with multi-sensor data fusion has led to significant progress in reducing motion artifacts and improving signal-to-noise ratios. These improvements are fundamental in challenging environments, such as during high-intensity physical exercises or in clinical settings where patient movement can be unpredictable.

3.2.3 Applications in prosthetic control and rehabilitation

EMG-based wearable sensors have become a cornerstone technology in the fields of prosthetic control and rehabilitation. By capturing subtle differences in muscle activation patterns, these sensors enable intuitive control of prosthetic limbs, thereby restoring a degree of natural movement to amputees. In addition, they allow for real-time monitoring of muscle fatigue and changes in neuromuscular coordination, which are critical for optimizing training regimens and rehabilitation protocols. Clinical studies have demonstrated that integrating EMG feedback into rehabilitation programs accelerates recovery by providing patients with immediate, quantitative feedback on muscle performance. This feedback, in turn, facilitates the personalization of therapies and the fine-tuning of exercises to address unique

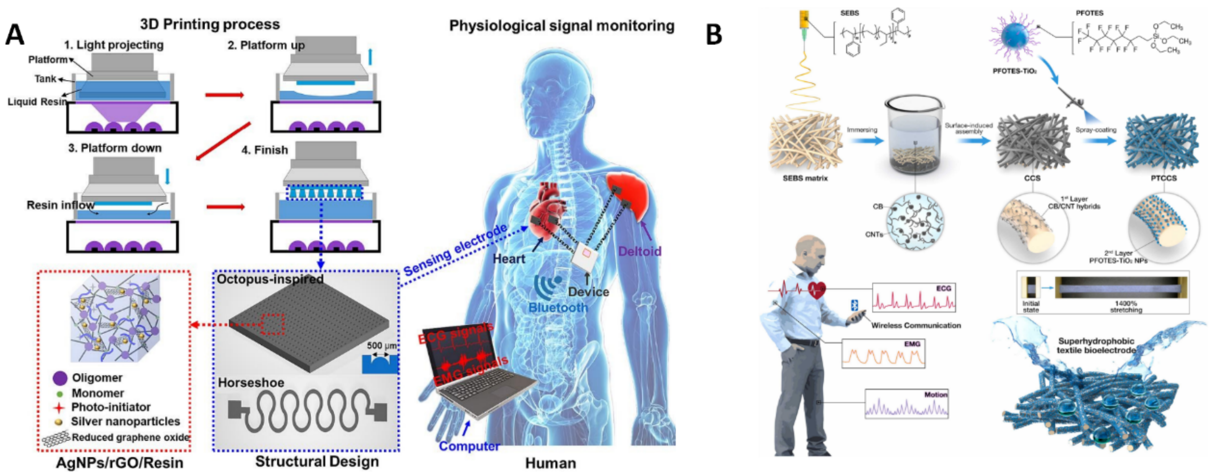

Figure 7. (A) Photocurable 3D-printed AgNPs/Graphene/Polymer nanocomposites for EMG smart clothing. Reproduced with permission [78]; (B) Carbon black nanoparticle/CNT (CB/CNT) stretchable conductive networks and superhydrophobic perfluorooctyltriethoxysilane modified TiO_2 nanoparticles (PFOTES-TiO_2 NPs) for EMG. Reproduced with permission [79]].

patient needs [97, 98]. Furthermore, the noninvasive nature of sEMG sensors, along with their ease of integration into wearable formats, makes them ideally suited for continuous, long-term monitoring in both clinical and everyday environments. The versatility of EMG sensors extends beyond conventional rehabilitation. Their ability to detect rapid changes in muscle activation patterns has also been leveraged in sports science to enhance athletic performance and reduce the risk of injury by monitoring fatigue levels and muscle imbalances during training sessions.

3.3 Brain-computer interface (BCI) for motion intention prediction

3.3.1 EEG and NIRS-based motion intention detection

The field of brain-computer interfacing has experienced rapid growth, particularly in applications aimed at predicting human motion intention. Electroencephalography (EEG) offers a noninvasive means to measure the electrical activity of the brain, thereby providing real-time insights into the neural processes underlying motor planning and execution. By decoding specific EEG patterns, researchers can interpret the user's intended movement even before any overt physical action is taken. This capability is especially valuable in the development of assistive devices, where real-time control is paramount. Complementing EEG, near-infrared spectroscopy (NIRS) is used to monitor hemodynamic responses by measuring changes in blood oxygenation levels within the cerebral cortex. While NIRS offers lower temporal resolution compared with EEG, it provides critical spatial and metabolic information which can enhance the interpretation of neural signals related to motion. Together, these modalities enable a comprehensive analysis of motion intention-which is essential for the deployment of systems in which rapid decision-making and precise control are required [7, 99].

Ongoing research in this area has demonstrated that by combining EEG and NIRS data with advanced machine learning algorithms, it is possible to accurately decode motion intention within milliseconds. Such systems hold promise not only for controlling prosthetic devices and exoskeletons but also for applications such as interactive gaming, neurorehabilitation, and remote-controlled robotic surgery. The translation of these innovations into wearable devices is gradually overcoming challenges related to signal attenuation, noise, and long-term user comfort.

3.3.2 Advances in dry electrodes and flexible sensors

A major challenge in the broader adoption of EEG and NIRS for wearable applications has been the need for comfortable, reliable, and noninvasive sensor interfaces. Traditional gel-based electrodes, while providing good conductivity, are prone to skin irritation and require frequent replacement. Recent innovations in dry electrode technology have dramatically improved user comfort and signal quality. These dry electrodes are inherently flexible and can conform to the contours of the scalp, ensuring consistent contact even during vigorous movements [44]. For example, Li et al. [94] presented a novel EEG electrode design combining few-layer graphene (FLG) with TiO_2 nanotube arrays for brain-computer interface applications. The researchers developed the electrode through electrochemical anodic oxidation and DC arc plasma jet chemical vapor deposition techniques (figure 8). The resulting FLG/TiO_2 electrode demonstrated several advantageous properties compared to

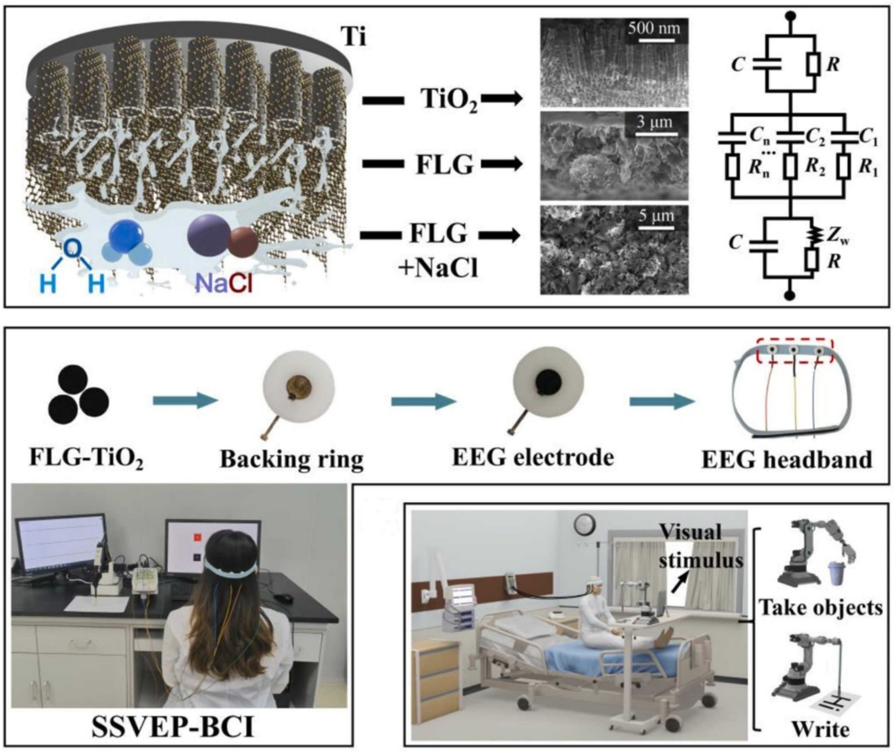

Figure 8. The response mechanism of EEG depends on the surface morphology and structure of electrodes. Assembly process of EEG headband and an experimental scene. A virtual expression, the patient with the EEG headband controls the robot arm to write. Reproduced with permission [94].

conventional gel-based Ag/AgCl electrodes. The electrode exhibited low scalp-contact resistance (9.2 – 19.0 kΩ) due to the synergistic effect between the FLG layer's ion adsorption/electron transfer networks and the TiO_2 nanotube array's electron transport capabilities. In performance testing, it showed higher signal amplitude and signal-to-noise ratio than commercial electrodes, while maintaining stability in both continuous and long-term usage. The electrode successfully detected 16 different stimulus frequencies in steady-state visually evoked potential (SSVEP) paradigm testing. Most notably, the researchers demonstrated practical application by incorporating three FLG/TiO_2 electrodes into an EEG headband system. Users were able to control a robotic arm to write various letters with high accuracy through brain wave signals. This achievement suggests significant potential for the electrode's use in brain-computer interfaces and other bioelectric applications, including ECG, EMG, and EOG monitoring in wearable smart devices.
In parallel, the integration of flexible substrates and stretchable electronics has led to the emergence of next-generation wearable biosensors that can be seamlessly incorporated into headgear, helmets, or even directly onto the skin. Such innovations have significant implications for long-term monitoring and real-time neurofeedback systems, where signal stability and user comfort are paramount. The convergence of nanomaterial innovation with advanced signal acquisition techniques not only enhances the performance of BCIs but also drives down production costs-making these systems more accessible for clinical and consumer applications.

3.3.3 Deep learning and transfer learning for MIP

Decoding motion intention from brain signals is an immensely challenging task due to the inherent complexity and variability of neural data. Deep learning models-such as convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and Transformer architectures-have demonstrated remarkable effectiveness in capturing the subtle spatiotemporal patterns within EEG and NIRS data. These models can automatically extract high-level features from raw sensor inputs, thereby obviating the need for manual feature engineering and significantly enhancing prediction accuracy. Recent work in this area has applied transfer learning techniques to adapt pre-trained deep learning models to new subjects or tasks with minimal retraining. This adaptability is critical for developing generalized motion intention prediction (MIP) systems that perform robustly across different populations and environmental conditions [7, 100]. The integration of these advanced computational approaches with wearable BCI systems paves the way for real-time applications that range from neurorehabilitation to intelligent prosthetic device control, fundamentally altering the way human–machine interfaces are conceived and deployed.

3.4 Emerging nanotechnology-based sensors

3.4.1 Triboelectric nanogenerators (TENGs)

Among the most exciting breakthroughs in the field of wearable sensors is the development of triboelectric nanogenerators (TENGs). TENGs exploit the triboelectric effect to convert mechanical energy, such as that generated during human movement, into electrical energy. This dual functionality-serving as both an energy harvester and a sensor-positions TENGs as a powerful tool for designing self-powered wearable devices. By eliminating the need for external batteries and power management systems, TENG-based sensors offer significant advantages in terms of device miniaturization, lightweight design, and long-term sustainability [6, 101]. Figure 9 shows the basic TENG design with its four modes.
TENG sensors are particularly well suited for applications that demand rapid response times and high sensitivity to mechanical stimuli. Ongoing research is focused on optimizing the material compositions and structural configurations of TENG devices to enhance their sensitivity and stability under variable environmental conditions. Recent developments in nanostructuring and surface engineering have enabled the production of TENGs with exceptional performance characteristics, opening new avenues for applications in both healthcare monitoring and environmental sensing.

3.4.2 Piezoelectric and bioelectric sensors

Piezoelectric sensors have long been recognized for their ability to convert mechanical stress into electrical signals, and recent advances in nanotechnology have further enhanced their performance in wearable applications. Figure 10 shows the four types of piezoelectric materials. Piezoelectric fiber composites, for instance, have been developed

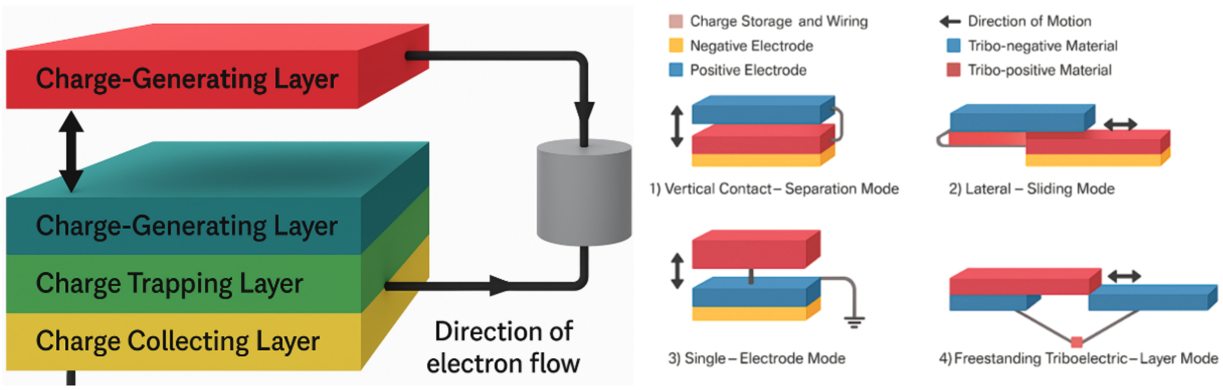

Figure 9. Basic TENG design by operating layer and the four basic TENG design modes.

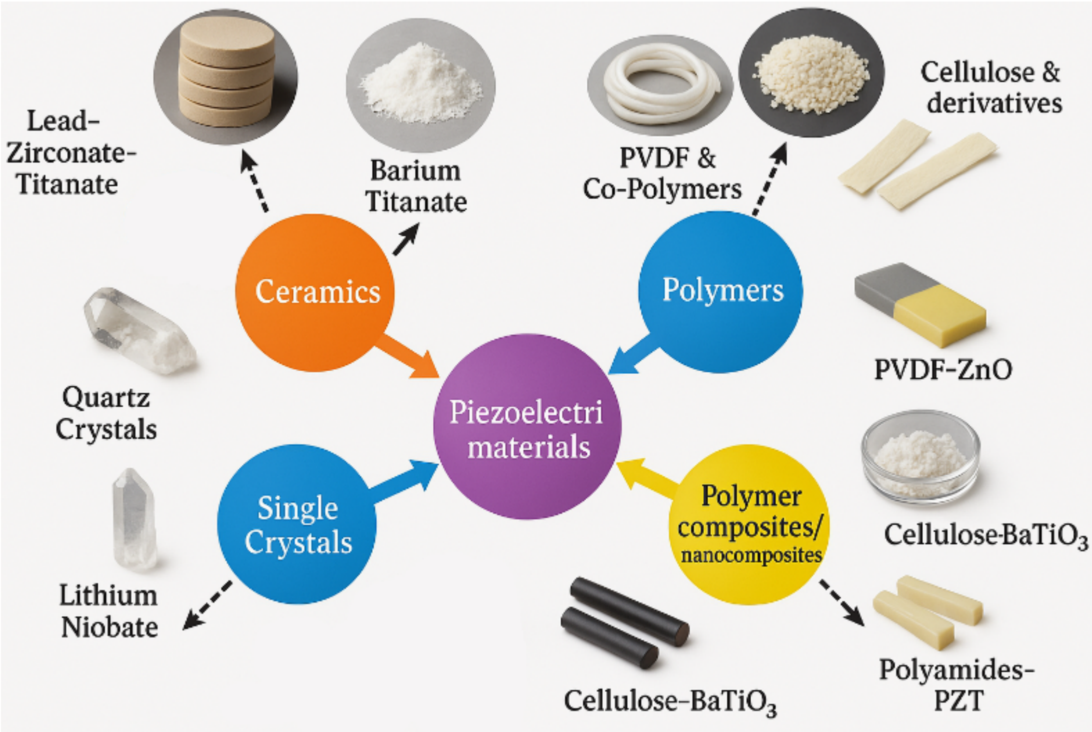

Figure 10. Classification of four types of piezoelectric materials.

to harvest energy from minute mechanical deformations associated with human motion, and they are now being considered as integral components of wearable energy-harvesting systems. Their integration into soft, conformal substrates has led to the creation of wearable electronic skins (e-skins) that provide not only pressure sensitivity but also the ability to monitor dynamic changes in posture and movement [21]. In addition to their energy-harvesting capabilities, piezoelectric sensors are inherently sensitive to stress and strain, making them suitable for a wide range of bioelectric sensing applications. The integration of such sensors into wearable platforms facilitates real-time monitoring of subtle physiological signals, such as pulse, joint angles, and muscle contractions. This convergence of piezoelectric and bioelectric sensing within a compact, wearable format is driving innovation in diagnostic devices, rehabilitation tools, and human-machine interfacing systems.

3.4.3 Graphene-based electronic tattoos (GETs)

The emerging class of graphene-based electronic tattoos (GETs) represents a paradigm shift in wearable sensor technology. These ultra-thin, skin-conformal devices are developed using advanced printing techniques and nanostructured graphene materials, which combine exceptional electrical conductivity with mechanical pliability. GETs are designed to adhere seamlessly to the skin, capturing high-fidelity electrophysiological signals and subtle changes in skin deformation with minimal interference to the wearer's natural movements.
Recent progress in inkjet-printed wearable nanosystems has illustrated the feasibility of fabricating self-powered, ultrathin sensors that operate reliably in various environmental conditions [15]. The unique mechanical and electrical properties of graphene allow GETs to maintain intimate contact with the skin, even during vigorous physical activities. This ensures continuous, high-quality data acquisition, which is critical for applications such as long-term health monitoring, emotion recognition, and biofeedback-assisted training. The flexibility and ultralight characteristics of GETs render them almost imperceptible to the user, thereby improving compliance and expanding the range of applications in wearable biomedical devices.
The development of GETs is also bolstered by their compatibility with various power-harvesting modalities, including TENGs and piezoelectric sensors. Such synergies between different nanotechnology-based sensor platforms not only enhance overall system performance but also pave the way for the creation of fully autonomous, self-powered wearable devices [102–104]. By integrating multiple sensor types into a unified system, researchers are moving closer to realizing next-generation wearable sensor networks that can continuously monitor and analyze complex human physiological and biomechanical parameters without the need for cumbersome external power sources.
Table 2 shows the comparative evaluation of emerging nanotechnology-based wearable sensors, which presents a side-by-side analysis. To facilitate a clearer understanding of the respective strengths and limitations of each sensor type, Table 3 presents a comparative summary highlighting their performance, applicable scenarios, and common algorithmic approaches used in signal processing and interpretation.

Table 2. Comparative evaluation of emerging nanotechnology-based wearable sensors.

Sensor Type	Sensing Mechanism	Signal Output	Power Source	Flexibility	Biocompatibility	Best Use Case	Key Limitation
TENG	Triboelectric effect	AC Voltage	Self-powered	High	Moderate	Dynamic, high-motion detection	Susceptible to humidity
Piezoelectric	Stress-induced charge	AC/Impulse	Self-powered	Medium	High	Pulse/strain monitoring	Limited stretchability
GET	Resistance change	DC signal	Requires external/interfaced power or integration with harvesters	Very High	Very High	Long-term skin-mounted biosensing	Fragile under repetitive strain

4. Multimodal approaches for enhanced accuracy and robustness

Nanotechnology-based wearable sensors have transformed the field of human motion and posture detection by enabling ultra-sensitive, low-power, and flexible sensing platforms. To further improve the accuracy and robustness of these systems, recent research has increasingly leveraged multi-modal approaches. By combining data from various sensing modalities-such as IMU, EMG, and BCI signals-with advanced deep learning algorithms, researchers have achieved substantial progress in real-time motion intention prediction and its applications. In this chapter, we discuss state-of-the-art sensor fusion techniques, deep learning models for multimodal feature integration, real-time applications in human-robot collaboration and prosthetic control, as well as the challenges and limitations associated with these approaches.

4.1 Sensor fusion techniques

4.1.1 Fusion of IMU, EMG, and BCI for motion analysis

Integrating heterogeneous sensor data-specifically from IMU, EMG, and BCI systems-has been shown to significantly enhance the accuracy of motion analysis and intention prediction. IMU sensors provide valuable data regarding acceleration, angular velocity, and orientation; however, they are often susceptible to drift and external disturbances. Meanwhile, EMG sensors capture the electrical activities of muscles, providing insights into muscle activation patterns that precede mechanical movement. BCI signals, often obtained through non-invasive EEG recordings, allow for the detection of motor intentions even before overt movement occurs. The fusion of these modalities creates a hybrid sensing system that leverages the strengths of each sensor type while mitigating their individual limitations [99, 105]. Recent studies have demonstrated that fusing IMU, EMG, and BCI data not only improves the precision of motion classification but also allows for anticipation of movement in its earliest phase [106]. For example, wearable bracelets have been developed that incorporate multiple sensing modalities to capture fine-grained muscular activity and inertial information concurrently. Such devices, by synchronizing these diverse signals, can resolve ambiguities that might arise when using a single sensor type-for instance, distinguishing between voluntary muscle contractions and involuntary tremors. This sensor fusion approach supports improved motion intention prediction, which is critical for applications in gesture recognition and early detection of user intent [107]. The combined use of these sensors creates opportunities for advanced motion analysis in diverse scenarios, ranging from industrial safety monitoring to prosthetic control. The integration framework typically involves preprocessing steps such as signal filtering and normalization, followed by alignment in the temporal domain to ensure that the signals from different modalities are synchronized. In a typical implementation, the IMU signal might be used to provide

Table 3. Comparative summary of wearable sensor types for human motion and posture detection, highlighting their key signal modalities, advantages, limitations, common application scenarios, and representative signal processing algorithms.

Sensor Type	Key Signal	Advantages	Limitations	Typical Applications	Common Algorithms
IMU (Inertial Sensors)	Acceleration, Angular Velocity	High temporal resolution; compact form factor	Susceptible to drift and noise	Motion tracking, industrial safety, fall detection	Kalman filter, Complementary filter, Adaptive filtering
EMG (Electromyography)	Bioelectrical muscle signals	Captures neuromuscular activation; intuitive control input	Sensitive to crosstalk, skin-electrode impedance issues	Prosthetic control, rehabilitation monitoring	Wavelet transform, Time-frequency analysis, CNN, LSTM
BCI (EEG/NIRS)	Neural activity, Hemodynamic signals	Predictive motion intent; non-contact control	Low signal-to-noise ratio; high latency	Assistive robotics, neurorehabilitation, VR/AR interfaces	CNN, Transfer learning, SSVEP decoding, CSP (Common Spatial Patterns)
Nanotechnology-based (TENG, Piezoelectric, GETs)	Mechanical-to-electrical transduction	Self-powered; ultrathin and flexible; skin-conformal	Environmental sensitivity, durability	Wearable e-skins, real-time strain sensing	Signal thresholding, Machine learning classifiers, FFT

the primary motion context, while the EMG signal refines the understanding of underlying muscle activity and the BCI data offers predictive insights regarding the initiation of movement. This complementary fusion allows for a robust estimation of motion parameters even under conditions of noisy measurements and environmental perturbations [108, 109]. A direct comparison reveals that IMUs excel in capturing gross limb dynamics with low latency (< 10 ms), but are prone to drift. EMG sensors provide earlier motion initiation signals (latency $\sim 50-100$ ms before movement onset) and offer better contextual muscle-specific activation profiles. BCIs, while slower in signal onset ($\sim 200-300$ ms), uniquely enable pre-motor intention decoding, which is critical for assistive robotics. Sensor fusion frameworks leveraging these modalities have achieved motion prediction accuracies above 95% in laboratory studies, outperforming single-sensor systems by $10-20\%$ in noisy, real-world conditions [106].

Such multimodal sensor fusion techniques are not only limited to laboratory demonstrations but are also increasingly being implemented in practical applications. For instance, in physical rehabilitation scenarios, the fusion of EMG and IMU data allows clinicians to monitor the progress of patients and adjust therapy regimens in real time [110]. The early detection offered by combining BCI signals with peripheral sensor data further opens possibilities for predictive intervention, which is essential in preventing injuries among industrial workers and enhancing the responsiveness of assistive devices [111, 112].

4.1.2 Deep learning for multimodal feature integration

In recent years, significant advances in deep learning have catalyzed the development of sophisticated models for multimodal feature integration in human motion sensing. Among these, CNNs and LSTM networks have been widely adopted for learning spatial and temporal features from synchronized IMU, EMG, and EEG data streams. For example, a typical CNN-LSTM hybrid architecture uses 1D convolutions (kernel size $= 3$, filters $= 64$) for temporal feature extraction from each modality, followed by LSTM layers (hidden units $= 128$) to model time dependencies. These are concatenated at the fusion layer and fed into fully connected layers for classification or regression tasks [113]. In addition, Transformer architectures with self-attention mechanisms have shown superior performance in modeling long-range temporal dependencies and inter-sensor interactions. For instance, a sensor-level transformer encoder with 4 attention heads and 2 encoder layers has been employed to fuse EMG and IMU signals, achieving classification accuracies exceeding 95% for complex motion tasks like gait phase detection and fall prediction [114].

CNNs have been particularly effective in extracting hierarchical features from time-series sensor data [115, 116]. When combined with recurrent layers or temporal convolution techniques, CNN-based models are capable of capturing intricate variations in motion patterns across different sensor domains [117]. In parallel, Transformer models have shown promise in modeling long-range dependencies and dynamic interactions among sensor signals, thereby accommodating the varying delays and sampling rates often encountered in wearable systems. The self-attention mechanisms inherent in Transformers enable the model to assign different weights to signals depending on their context, leading to more nuanced and accurate motion intention predictions [118].

Differentiable Bayesian filtering architectures represent another promising avenue for multimodal feature integration. By incorporating sensor uncertainty into the learning framework, these methods can robustly fuse information from multiple sensors even when measurement noise is high. Such architectures maintain the interpretability of traditional Bayesian filters while benefiting from the capacity of deep learning models to learn complex, non-linear relationships [119]. Moreover, ensemble methods combining CNNs, Transformers, and differentiable filtering modules have exhibited notable improvements in real-time systems, reducing false positives and achieving higher sensitivity under dynamic conditions [15].

The rapid development of these deep learning architectures has facilitated the transition from prototype laboratory systems to integrated wearable solutions. By continuously refining these models with larger, real-world datasets, researchers are steadily overcoming challenges related to sensor variability and environmental interference, paving the way for robust, end-to-end system deployments in everyday applications [120].

4.2 Real-time motion intention prediction and applications

The ability to predict human motion intention in real time serves as a cornerstone for a variety of applications, ranging from human-robot collaboration in industrial settings to advanced prosthetic and exoskeleton control systems. Such real-time predictions are made possible by the seamless synthesis of multimodal sensor data coupled with deep learning algorithms that process and integrate features in real time.

4.2.1 Human-robot collaboration and industrial safety monitoring

Human-robot collaboration environments demand high levels of adaptability and rapid response capabilities to ensure both operational efficiency and worker safety. In industrial applications, real-time motion intention prediction can be employed to monitor worker activities and predict hazardous movements before they occur, thereby reducing the risk of accidents [121, 122]. Enhanced safety protocols are achieved by integrating multimodal sensor data that continuously tracks user posture, gait, and other motion parameters [109].

Several studies have demonstrated the efficacy of multimodal fusion methods in projecting precise motion intentions for industrial tasks. For instance, sensor fusion strategies that combine IMU readings with EMG data have enabled the early detection of abnormal movements or fatigue-related declines in performance. This early detection facilitates timely intervention by automated systems or human supervisors, which can halt dangerous operations or adjust robotic actions accordingly [123]. Moreover, deep learning models trained on extensive datasets from industrial environments have shown high generalization performance, even in the presence of significant environmental variations [124].

Real-time data processing in these environments is critical. The fusion algorithms not only have to rapidly synthesize data from various sensors but must also be computationally efficient to be run on embedded systems with limited processing power [125–127]. Advances in edge computing, along with lightweight deep learning architectures, have enabled the realization of robust, real-time prediction systems [128]. These systems have been successfully deployed in environments such as automotive assembly lines, where they monitor complex human-machine interactions to reduce accidents and improve overall process efficiency [129].

4.2.2 Prosthetic control and exoskeleton assistance

Another important application of real-time motion intention prediction is in the realm of prosthetic control and exoskeleton assistance. In these contexts, precise decoding of the user's intended movements is essential to enable fluid and natural interactions between the human and the device [130, 131]. Multimodal sensor fusion is employed to capture subtle variations in muscle activation and mechanical kinetics, thereby facilitating fine-tuned control of prosthetic limbs or exoskeletons [6].

Research in this area has long benefited from pioneering studies on ambulatory knee-ankle-foot orthoses (KAFOs), which laid the groundwork for subsequent advances in sensor-equipped prostheses [132]. More recently, wearable systems have been integrated with magnetic induction sensors and nanostructured materials to further reduce latency and enhance precision in control feedback. For instance, new sensor designs incorporating nanogenerators and flexible printed circuits have allowed for the creation of prosthetic devices that dynamically adjust performance based on the user's real-time intent [133].

Additionally, training algorithms that utilize deep neural networks to integrate features from EMG, IMU, and even tactile sensors have led to substantial improvements in the responsiveness and accuracy of exoskeleton devices, which are employed both in rehabilitation and in augmenting physical performance. These advances not only improve the functional outcomes for users but also enhance the overall safety, enabling seamless interaction between humans and assistive technology [70]. In addition to exoskeletons and prosthetics, a promising frontier lies in the integration of wearable sensors into soft robotic suits-flexible exo-wearable platforms designed to assist or augment human movement. These systems require high-fidelity motion capture and low-latency feedback, both of which are supported by nanomaterial-based sensors with excellent mechanical compliance and rapid response. Recent prototypes incorporate strain sensors based on carbon nanotubes or graphene into soft actuators to provide closed-loop proprioceptive feedback in real time [134]. Moreover, wearable sensors are increasingly being embedded into human-computer interaction (HCI) systems to enable intuitive control via gesture, facial muscle movement, or even brain activity. This is particularly relevant in virtual and augmented reality environments, where real-time posture tracking can support immersive navigation and control interfaces [135]. Another emerging direction involves haptic feedback integration, where sensors and actuators work synergistically to provide users with tactile cues-thereby improving interaction fidelity in robotic control, rehabilitation training, and telepresence systems [136]. These multidisciplinary applications highlight the transformative potential of wearable nanotechnology beyond traditional biomedical monitoring, further bridging the gap between humans and intelligent machines.

The integration of deep learning models with multimodal sensor systems in prosthetic and exoskeleton applications also addresses the challenge of adapting to individual user variability. Adaptive algorithms, which learn from the user's movement patterns over extended periods, continuously update the control parameters, thereby providing personalized assistance that evolves with the user's rehabilitation progress [137].

4.3 Challenges and limitations

Despite significant progress in multimodal sensor fusion for motion and posture detection, several challenges and limitations persist. Addressing these issues is critical for the translation of laboratory prototypes into robust, real-world applications.

4.3.1 Synchronization and data latency issues

One of the foremost challenges in multimodal sensor fusion is achieving precise synchronization among the diverse sensor modules. Since data are acquired at different sampling rates and with variable latencies, misalignment of signals can lead to erroneous fusion results. This is particularly problematic in applications requiring rapid response times, such as real-time motion intention prediction for industrial safety monitoring and prosthetic control [138].

Several techniques have been proposed to address synchronization issues, including time-stamping of sensor data, precise hardware clock synchronization, and advanced signal processing algorithms that align data streams post hoc [139]. Nonetheless, latency remains a critical bottleneck, especially when fusing high-frequency signals such as those from EMG sensors with lower frequency BCI data. The latency introduced by deep learning inference on resource-constrained wearable devices further exacerbates the issue, necessitating continuous efforts to optimize both algorithmic efficiency and sensor hardware [119].

4.3.2 Motion artefacts and environmental noise

Wearable sensors are invariably exposed to motion artefacts and environmental noise, which can significantly degrade the quality and reliability of the acquired signals. Motion artefacts, often caused by sensor slippage, mechanical vibrations, or abrupt movements, introduce unwanted fluctuations in the EMG and IMU signals. Similarly, environmental factors such as electromagnetic interference, temperature fluctuations, and ambient light variations can corrupt sensor readings [5].

To mitigate these issues, robust signal processing techniques-such as adaptive filtering, noise reduction algorithms, and sensor calibration routines-have been incorporated into multimodal fusion strategies. Deep learning models, in particular, have demonstrated improved resilience against noise due to their ability to learn invariant features from corrupted data [117]. However, the performance of these techniques is still highly dependent on the quality of the training data, and careful dataset curation remains essential to ensure that models are robust to a wide range of noise sources [113].

Furthermore, the design of wearable sensors often involves trade-offs between sensitivity and noise immunity. For instance, while high-sensitivity sensors are capable of detecting minute physiological signals, they are also more prone to interference from ambient noise. Balancing these conflicting requirements poses a continuing challenge in the field, particularly for applications involving long-term monitoring where sensor drift and degradation can further impact performance [120].

4.3.3 Wearability and long-term data collection constraints

Wearability constitutes another critical challenge in the deployment of nanotechnology-based wearable sensor systems. The effectiveness of these devices is not solely determined by their sensing capabilities but also by factors such as user comfort, aesthetic integration, and the facility for long-term data collection. Flexible, lightweight, and unobtrusive sensor designs are essential for ensuring user compliance, especially in applications that require continuous monitoring over extended periods [6].

One of the inherent difficulties in long-term wearable sensor deployment is the gradual degradation of sensor performance due to factors such as biofouling, mechanical wear, and environmental exposure. Moreover, the integration of multiple sensor modalities further complicates the device design, as each sensor may have distinct power requirements, operational lifespans, and maintenance needs [18].

Innovative nanomanufacturing techniques such as inkjet printing and 3D fabrication have been introduced to address these wearability constraints by enabling scalable, cost-effective production of flexible sensor components [15]. However, despite these advances, issues such as sensor drift, data loss during long-term operation, and variations in sensor positioning relative to the skin or target muscles continue to challenge system reliability. These issues are particularly pronounced in dynamic environments where user motion and microclimatic changes may alter sensor contact characteristics [139].

Researchers are actively exploring self-calibration algorithms and adaptive signal processing techniques that can compensate for sensor drift over time. In parallel, battery-free or self-powered sensor designs based on nanogenerators are being investigated as a means to support continuous, long-term operation without the need for frequent recharging or battery replacement [6, 140].

Moreover, the challenges associated with wearability are not limited to hardware constraints. User acceptance and behavioral factors, such as the ease of donning/doffing the device, comfort during physical activity, and psychological impacts of wearing conspicuous sensors, also play a decisive role in the success of long-term monitoring systems. Studies addressing these human factors have provided valuable insights that inform the iterative design process for next-generation wearable technologies [132, 141].

Addressing both the technical and human-centric challenges associated with wearable multimodal sensor systems remains an ongoing area of research. Future work must continue to push the boundaries of sensor miniaturization, energy efficiency, and data fusion accuracy while ensuring that the devices remain comfortable and unobtrusive for long-term use [142, 143].

4.3.4 Regulatory, ethical, and commercialization considerations

The deployment of wearable sensor technologies, particularly in healthcare and workplace environments, is closely tied to regulatory, ethical, and commercial pathways. First, regulatory frameworks such as those governed by the U.S. Food and Drug Administration (FDA), European CE marking, and ISO 13485 require that wearable medical devices undergo extensive validation for safety, biocompatibility, and performance consistency. These requirements can be time-consuming and costly, particularly for multifunctional nanomaterial-based sensors whose long-term biological effects may remain under-investigated [144].

Ethical issues also arise, especially in relation to data collection, consent, and surveillance. Wearable systems that continuously monitor biosignals raise concerns over data privacy, ownership, and potential misuse. Compliance with frameworks such as the general data protection regulation (GDPR) is necessary to ensure user autonomy and protect sensitive biometric information [145]. Moreover, in workplace or sports contexts, ethical dilemmas may emerge over coercion or pressure to adopt monitoring technologies, potentially infringing on individual rights or creating biased performance assessments.

On the commercialization front, challenges include bridging the gap between lab-scale prototypes and scalable, market-ready products. Factors such as manufacturing costs, durability under real-world use, integration with existing digital infrastructure (e.g., smartphones, cloud platforms), and reimbursement eligibility (for clinical applications) influence adoption rates. While venture investment in wearable biosensors is growing, product-market fit and user acceptability remain decisive for sustained commercialization [146].

4.3.5 Environmental durability and longevity under real-world conditions

In real-world applications, wearable sensors are subject to a variety of environmental and physiological stresses that can degrade their performance over time. These include mechanical fatigue due to repeated motion, prolonged exposure to sweat and moisture, and temperature variations associated with outdoor or athletic use. Addressing these challenges is critical for the practical deployment of wearable systems in healthcare, sports, and industrial settings. Recent studies have demonstrated that mechanical cycling-such as repeated stretching or bending-can cause delamination, crack propagation, or loss of conductivity in nanomaterial-

based sensors if not properly encapsulated or reinforced. For instance, graphene and silver nanowire-based sensors have shown electrical drift after more than 1000 cycles of 20% tensile strain unless protected by elastomeric coatings or embedded in stretchable matrices [147, 148].
Sweat exposure presents another significant challenge due to its salt content, acidity, and long-term corrosive effects. To mitigate this, researchers have developed hydrophobic or sweat-resistant coatings, such as PDMS or fluorinated silanes, which help maintain signal integrity over prolonged skin contact [149]. Some efforts also incorporate super-hydrophobic and self-cleaning surfaces to reduce sweat-induced signal drift. Thermal fluctuations can affect both the sensor materials and the skin-sensor interface. Materials with mismatched thermal expansion coefficients can delaminate, and polymers may soften or stiffen across temperature ranges. Recent developments in thermally stable nanocomposites-such as CNT-elastomer blends and aramid nanofiber-reinforced matrices-have shown promise in maintaining performance from −20 °C to 80 °C in accelerated aging tests [150].
Therefore, the durability of wearable sensors under mechanical, thermal, and biochemical stressors remains an active research frontier. Ongoing work in encapsulation technologies, self-healing materials, and adaptive algorithms that compensate for drift and degradation will be crucial for ensuring long-term, real-world reliability.

5. Conclusion

The rapid evolution of nanotechnology-based wearable sensors has ushered in a new era of highly sensitive, flexible, and self-powered systems for real-time monitoring of human motion and posture. This review highlights the critical role of advanced nanomaterials, such as graphene, carbon nanotubes, and metal nanowires, in enhancing the mechanical flexibility, sensitivity, and biocompatibility of wearable sensors. The integration of these materials with innovative sensor designs and energy-harvesting technologies, such as triboelectric and piezoelectric nanogenerators, has enabled the development of self-powered devices that eliminate the need for external power sources, ensuring continuous operation in diverse environments. Furthermore, the incorporation of AI and machine learning algorithms has significantly improved the interpretation and classification of sensor data, enabling real-time motion intention prediction and adaptive responses to complex movement patterns. The review also explores advancements in fabrication techniques, including 3D printing, inkjet printing, laser scribing, and transfer printing, which have facilitated the production of scalable and cost-effective sensor systems [151]. These technologies have enabled the creation of ultrathin, flexible sensors that can conform to the human body, ensuring seamless integration into daily life. Moreover, the fusion of multiple sensing modalities, such as inertial sensors, EMG, and BCI, has led to the development of multimodal systems that enhance the accuracy and robustness of motion detection across various applications, including healthcare, rehabilitation, sports performance, and industrial safety. Despite remarkable progress, challenges such as sensor stability, environmental interference, and long-term durability remain. Future research should focus on overcoming these limitations while advancing the scalability, accuracy, and user comfort of wearable systems [152]. By addressing these challenges, nanotechnology-based wearable sensors hold immense promise for transforming personalized healthcare, enhancing human-machine interactions, and paving the way for the next generation of smart, autonomous monitoring systems.

Authors Contribution
All the authors have participated sufficiently in the intellectual content, conception and design of this work or the analysis and interpretation of the data (when applicable), as well as the writing of the manuscript.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests
The author states that there is no conflict of interest.

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